

**EXPLORING THE RELATIONSHIP BETWEEN RESILIENCE AND
LEARNING STYLES AS PREDICTORS OF ACADEMIC
PERSISTENCE IN ENGINEERING**

A Dissertation

by

SHANNON DEONNE WALTON

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2010

Major Subject: Interdisciplinary Engineering

**EXPLORING THE RELATIONSHIP BETWEEN RESILIENCE AND
LEARNING STYLES AS PREDICTORS OF ACADEMIC
PERSISTENCE IN ENGINEERING**

A Dissertation

by

SHANNON DEONNE WALTON

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Chair of Committee,
Committee Members,

Head of Department,

Karan Watson
César Malavé
Christine Stanley
Jeffrey Froyd
Robin Autenrieth

December 2010

Major Subject: Interdisciplinary Engineering

ABSTRACT

Exploring the Relationship between Resilience and Learning Styles as Predictors of
Academic Persistence in Engineering. (December 2010)

Shannon Deonne Walton, B.S., Texas A&M University;

M.S., Texas A&M University

Chair of Advisory Committee: Dr. Karan Watson

In recent years, engineering education has witnessed a sharp increase in research aimed at the outcomes of academic success and persistence within engineering programs. However, research surrounding the key forces shaping student persistence remains unknown. This study explores enhancements and broader perspectives of learning; the relationship among dimensions of resilience theory and learning styles in engineering students to identify elements of both that contribute towards academic persistence and to determine which components of both contribute towards strengthening students' academic persistence in engineering.

The study was conducted using two quantitative self-reporting instruments to measure resilience and learning style preference, the Personal Resilience Questionnaire (PQR) and the Index of Learning Styles (ILS). Retention was measured as the continuous enrollment of a student into the second semester of the first-year engineering program.

Results indicate that the following have a statistically significant effect on student persistence in engineering programs at Texas A&M University: learning style construct *sequential*; resilience constructs *positive (self)* and *focus*; with both tools combined, *positive (self)*, *organized*, *positive (world)*, *flexibility (self)* and *focus*; and a newly combined construct, *Walton's self-efficacy*.

DEDICATION

Lovely Jean Henderson

This is for you!

I love you, Momma.

(1946-2004)

To my husband, my love, my best friend, Rashone Walton (“Bird”), deep within our friendship lies a love that shines. Thank you for being both proud and supportive of my work and sharing in the many uncertainties, challenges and sacrifices that came with completing this dissertation. I could not have done this without you. I love you.

To my Father, Ronald Henderson, whose love and support I have cherished throughout my life. You continued to emphasized the importance of education and nurtured my potential right from childhood. You pushed me beyond my fears and gave me the courage to persevere, leaving no stone unturned. This dissertation is evidence of the seeds that you and Momma sowed many years back. You are my hero!

To my step-children, Quadra and Quadarian Walton, never give up. Press toward the highest you can achieve. No man can keep from you what God has planned for you.

ACKNOWLEDGEMENTS

I know resilience. In fact, I AM RESILIENT. It has taken me nearly 10 years to complete the requirements for this terminal degree. It was during this experience that I encountered many valleys, and mountains seemed to encompass every turn.

One word makes this journey possible. That word is “JESUS!” He is the Power for whom I give glory, honor and thanks. With Him all things are, in fact, possible.

There are so many people to acknowledge for the inspiration to complete this chapter of my life. First I must thank my committee chair, mentor and friend, Dr. Karan Watson. Your faithful guidance, support, encouragement and belief in me have been invaluable throughout this long, long journey. You are priceless!

I would like to extend thanks to the rest of my committee members. Thank you to Dr. Jeff Froyd for agreeing to serve on my committee, for allowing me the opportunity to work with you and providing clear, crisp and succinct critiques enabling me to complete this study. Your eye for detail and dedication to learning will always be remembered as contributing to a better project result. With or without my dance, you are a class act! Thanks to Dr. César Malavé for providing insight and interest in my study. Dr. Christine Stanley, your patience and gently guidance continued to move me in the direction of my goal. Thank you, Soror.

I extend my appreciation to ConnerPartners for allowing me to use the Personal Resilience Questionnaire, scoring the questionnaire, and their timely response each time I contacted them.

My sincerest thanks go out to Mrs. Marilyn Green (MG). You have filled so many roles in my life; my second Mother, my mentor, my friend. When I wanted to throw my hands up and call it quits, your belief in me, along with your mesmerizing smile always seemed to make everything okay.

Special thanks to Dr. Karen Butler-Purry, my supervisor, my mentor, my Sister, my friend. Your input, unyielding support and encouragement provided along the way were very much appreciated.

I am grateful to the former Engineering Academic Programs Office (EAPO), current Engineering Student Services and Academic Programs (ESSAP) office and the Engineering Office staff, past and present – Teresa Wright (“Tree”), Toni Alvarado, Naomi Gomez, Lori Cardenas, Deanna Rodriguez, Jeanne Rierison, Jan Rinehart, Marsha Lee, and Ben Erdman – for all the assistance and encouragement provided during my tenure at Texas A&M University. I am deeply humbled and appreciative for all the kindness, efforts and encouragement during this process.

To my friends and family (in no particular order), old and new, that shared in this journey with me: Vaneshia, Tweet, Steph E., Rashida, Cassie, Tam, Curley, Lesliam, Dnyanesh, Nanc, Mel, Kelly, Sharonda, Dee, Monique, Jackie, Damali, Derek, Broussard, Steph A., Dooney, Tiff B., Tiff T., Beverly, Mary B., Dorcas, Becky, Kathy M., Alee (excuse me, Athena) M., Breedlove, Kevin Mac, Colby, Jess, Dumezie, Doug, Faith (Faye), Leslie, Nella, Tim S., Mr. B, Bev, Uncle Watson (both of them), Paulette (Lola Falana), Momma Mary, Mr. & Mrs. Rice, thank you, for your unconditional support and undying friendship.

To the Ladies of Delta Sigma Theta Sorority Incorporated, Brazos Valley Alumnae Chapter, thank you for the sisterhood and fellowship. A special congratulation goes out to my line sister, DeEtra Young, for also completing this journey. Oo-oop!!!

Most of all, I wish to express my love and deepest appreciation for the support and dedication my husband has given me. Bird, I am so fortunate to have a mate and best friend that loves me unconditionally. Together, the sky is the limit. This work would mean nothing without sharing it with you.

In conclusion, I express all the love, support and appreciation to my parents, Ronald and Lovely Henderson. Your greatest gift has always been the love and support you have given me. I will miss sharing this accomplishment with my Mother, but I am confident that she is shining endless smiles down on me.

TABLE OF CONTENTS

	Page
ABSTRACT	iii
DEDICATION	v
ACKNOWLEDGEMENTS	vi
TABLE OF CONTENTS	ix
LIST OF FIGURES	xi
LIST OF TABLES	xii
 CHAPTER	
I INTRODUCTION	1
Purpose of the Study	2
Motivation for the Study	2
Significance of the Study	3
Organization of the Study	4
II LITERATURE REVIEW	5
Persistence in Engineering	5
Persistence of Underrepresented Groups in Engineering	9
Resilience Theory	12
Learning Styles	15
Working Definition	16
III METHODOLOGY	17
Instrumentation	17
Population	35
Administration of Survey	36
Statistical Analysis	37

CHAPTER		Page
IV	PRESENTATION AND ANALYSIS OF DATA	39
	Descriptive Parameters of Sample Respondents	39
	Results of Data Analysis	49
	Discussion of Major Findings	71
V	SUMMARY AND CONCLUSIONS.....	74
	Overview	74
	Interpretation of Findings.....	75
	Implications.....	77
	Limitations of the Study	78
	Recommendations for Future Research	79
	REFERENCES	80
	APPENDIX A	92
	APPENDIX B	97
	VITA	98

LIST OF FIGURES

	Page
Figure 4.1 Recoded dimensions of the Index of Learning Styles	41
Figure 4.2 Frequency values for active-reflective style dimension	43
Figure 4.3 Frequency values for sensing-intuitive style dimension.....	44
Figure 4.4 Frequency values for visual-verbal style dimension.....	45
Figure 4.5 Frequency values for sequential-global style dimension.....	46
Figure 4.6 Frequency values for resilience indicators.....	48
Figure 4.7 Scree plot	64

LIST OF TABLES

	Page
Table 3.1 Summary of 6 major models of learning styles	27
Table 3.2 Summary of 3 major models of resilience theory	34
Table 4.1 Correlations for learning styles and student persistence (n=220)	50
Table 4.2 Model summary for Index of Learning Styles	51
Table 4.3 General Linear Model (GLM) for Index of Learning Styles	52
Table 4.4 Regression coefficients for Index of Learning Styles	53
Table 4.5 ANOVA for sequential-global learning style dimension	54
Table 4.6 Correlations for resilience and student persistence (n=314)	55
Table 4.7 Model summary for Personal Resilience Questionnaire	56
Table 4.8 ANOVA for Personal Resilience Questionnaire	56
Table 4.9 Regression coefficients for Personal Resilience Questionnaire	57
Table 4.10 Correlations for learning styles, resilience and student persistence (n=179)	59
Table 4.11 Model summary for Index of Learning Styles and Personal Resilience Questionnaire	60
Table 4.12 Regression coefficients for Index of Learning Styles and Personal Resilience Questionnaire	61
Table 4.13 ANOVA for Flexibility (social), Positive (world), Positive (self), and Focus with combined constructs of Index of Learning Styles and Personal Resilience Questionnaire	62
Table 4.14 Pattern matrix from factor analysis	66
Table 4.15 Component loadings	67
Table 4.16 Scaled groupings based on factor analysis	67

	Page
Table 4.17 Correlations for derived groupings	69
Table 4.18 Model summary for derived groupings	70
Table 4.19 Regression coefficients for derived groupings.....	71

CHAPTER I

INTRODUCTION

The United States' economy ranks among the strongest in the world, due in large part to its leadership in science and technology. However, the National Science Board's (NSB) 2006 *Science and Engineering Indicators* report, and other studies such as the well publicized *Rising Above the Gathering Storm* raises questions regarding whether the U.S. can maintain its scientific leadership in the future [1, 2]. Indications are that the long-term prospect of a competitive national economy currently depends on boosting participation and achievement in science and mathematics, and that pedagogical approaches – that is, how we educate students – has to become a national concern [3, 4].

According to the Bureau of Labor Statistics, jobs requiring science, engineering or technical training will increase 24 percent, to 6.3 million, between 2004 and 2014 [5]. This will be the country's engineering workforce; with individuals reaching traditional retirement age tripling during the next decade [6]. The science and engineering workforce must be ready to meet these demands; supplying employees with the required expertise, skills and knowledge. Failure to supply the quantity and quality of science and technology degree holders may cause employers to seek labor needs internationally and or moving offshore; resulting in a "spiraling situation that could jeopardize the future prosperity, global preeminence, and even national security of the United States [4]." In an era of scientific and technological advancements, higher education must evolve to

This dissertation follows the journal style of the *Journal of Engineering Education*.

meet these challenges and build a cohort of world-class talent in science, technology, engineering and mathematics (STEM) fields.

While the availability of engineering jobs is steadily increasing, the rate of production of undergraduate engineering graduates has declined, creating an increasing gap between the number of engineering positions available and the number of engineering graduates to fill them.

Purpose of the Study

The purpose of this study is to assess the relationship among dimensions of resilience theory and learning styles in engineering students and study how dimension of both influence academic persistence in engineering.

Motivation for the Study

A wide range of interventions have been adopted and designed for identifying, attracting, enrolling, supporting and graduating engineering students. The results indicate that interventions have enhanced the likelihood that students will persist; nevertheless, these intervention mechanisms propose a snapshot fix to the predicament of a waning persistence of students in engineering. There is a growing need for research that explores enhancements and broader perspectives of learning linked to student persistence in engineering. The impetus for conducting the study presented in this dissertation is to (1) find variables that may be useful in identifying students who may be at risk of leaving engineering and (2) to investigate the relationship between the said

variables that are essential to engineering persistence and the nation's global competitiveness.

Significance of the Study

Students' academic performance and continued enrollment are a concern for universities and their respective colleges, worldwide. Because it is more expensive to recruit students than it is to retain current students, growing attention has turned to identifying factors that will help identify those at risk of leaving an engineering major [7].

Traditionally, high school grade point average (GPA), academic achievement test (ACT), and standardized achievement test (SAT) scores have been used to predict those students who will or will not persist. Nonetheless, noted research has found that other factors such as ineffective skills for resolving problems, stress-coping factors, and poor social skills are better predictors of non-persistent students. This implies that measures of students' abilities to cope effectively with the college experience, their resilience, may be as or more important than measures of academic ability alone [8].

Although persistence is an interactive process and retention or persistence in college or engineering as a major has been studied extensively, such has not been studied from the perspective of learning style preference using the concept of resilience. By taking a non-traditional approach, we may learn that the relationship amid resilience and learning styles produces significant results. This research study explores the relationships between the two to better understand student persistence in engineering.

The results of this investigation will serve as a basis for a vital assessment of students' strengths and weaknesses, and contribute to the field of study in engineering education by combining, the concepts of resilience theory and learning styles on student persistence. With such awareness, it is possible to focus on significant factors and characteristics that effectively assist in the waning persistence of students in engineering and the increased performance of the graduating engineer.

Organization of the Dissertation

This dissertation is organized into five chapters. Chapter I explores the purpose and background for the investigation into persistence in engineering. Chapter II reviews the literature realms persistence, resilience theory and learning styles, all of which should be considered contributing factors related to the success of students in engineering. Chapter III discusses the methodology utilized to guide the research, data collection procedures, and analytical approaches. Chapters IV and V present the results, discussion, and implications of the findings to highlight the similarities and differences between and among participants for further research studies.

CHAPTER II

LITERATURE REVIEW

This chapter presents a review of the literature, establishing the foundation for the study of the relationships among dimensions of resilience theory and learning styles towards increasing student's persistence in engineering. As an alternative to traditional methods, the aim of this research is to examine resilience theory and learning styles to determine if they influence student persistence in engineering. The review of the literature related to this study encompasses three areas:

1. Undergraduate student persistence in engineering
2. The emergence of resilience theory as an educational phenomena, and
3. The learning style approach to engineering education.

Persistence in Engineering

Few fields in higher education have received as much attention as student persistence [9-14]. It is encouraging to know that student participation in college programs has increased, nevertheless, student enrollment and graduation rates in U.S. engineering programs have declined and attrition out of engineering is continually rising [2, 6, 15-17]. In 1975, attrition of engineering freshmen was 12 percent after the first year of enrollment, by 1990; it had double to over 24 percent [7, 18]. Ultimately, well-documented attrition rates suggest that typically 50% to 70% of the freshmen engineering students will not graduate with an engineering degree, and 40% of departing students will switch to non-science fields during their first year [19-21]. Astin reports that only 47 percent of freshmen who start their academic career in engineering actually graduate with an engineering degree [22]. According to *Engineering & Technology*

Degrees, 2007, a new report from the Engineering Workforce Commission (EWC), the number of baccalaureate degrees awarded in engineering dropped slightly in 2007 to 75,486, a 0.8% decline from 76,103 in 2006 [23]. These numbers are a cause for concern, and to date most of what has been discovered from the research are factors that explain student non-persistence, while many of the factors influencing persistence have yet to be fully researched [8, 21].

The *2006 Science and Engineering Indicators*, published by the National Science Foundation, indicates that science, technology, engineering and mathematics (STEM) students' persistence-to-graduation rate is about the same as non-STEM students [24]. In addition, a recent study found that students who leave engineering are not academically different from those who stay; both sharing similar academic experiences [15, 17, 25].

Influencing factors of high student attrition rates in engineering surrounds the phenomenon that most of those who leave engineering lack the needed academic ability. However, data shows that only a small portion, 8.5%, of engineering students leave due to academic difficulty [26, 27]. For example, studies investigating students' high school GPAs have shown little difference in academic status between students who persist and those who do not [15, 17, 19, 28]. This finding postulates that the issue here is the loss of highly qualified students both before and after STEM enrollment.

Research proposes numerous explanations for the lack of student persistence in engineering. These prevailing theories suggest that student persistence is a function of student attributes as well as institutional fit [16, 22, 29-31].

A popular theory poised by Vincent Tinto, a leading authority on student persistence, acknowledges that the majority of assistance provided to influence

persistence is rooted in retention programs. Tinto postulates that this approach only “enhances the likelihood” of persistence to degree attainment by focusing on the actions and responsibilities of the institution and less on the actions of the students, resulting in limited impact [21]. As a result, comparable changes in the academic or organizational aspects have yet to be seen; leaving the educational experiences of students “largely unchanged [21].”

For decades, researchers have been expanding, critiquing, and refining the empirical base supporting Tinto’s influential model of student departure. Using longitudinal data, Tinto’s theory states that, to persist, students need integration into both formal and informal academic and social systems [21].

Tinto’s model of institutional departure is centered on the notion of integration: a student enters higher education with a set of background characteristics, intentions and expectation, and his or her decision to persist or depart [21]. Tinto suggests that the early intentions and commitments that students make to both their academic and career goals determines whether or not persisting outweighs the benefits of persisting [13].

Astin’s theory of student involvement, examines what he refers to as the theory of student development. He defines it as the amount of physical and psychological energy that a student devotes to the academic and social aspects of college life [32]. Similar to Tinto, Astin proposes that student interactions with both academic and social aspects of college life affect retention. According to Astin, “a highly motivated student is one who, for example, devotes considerable energy to studying, spends a lot of time on campus, participates actively in student organization, and interacts frequently with faculty members and other students. Conversely, an uninvolved student may neglect

studies, spend little time on campus, abstain from extracurricular activities, and have little contact with faculty members or other students [32].” This theory provides the framework of developmental theory in higher education, giving equal emphasis to teaching, research and student support services, supporting Tinto’s claim that involvement strongly influences a student’s retention and academic and psychological development.

Astin, while not negating the psychological or motivational aspects of student involvement, emphasizes the behavioral aspect of involvement. The student involvement theory places the student at the center of the learning process.

A cross-institutional study by Besterfield-Sacre et. al found that student attitudes and perceptions, about engineering and about themselves, can provide an effective means for predicting student persistence [19]. They found that freshmen engineering students who left the program in good standing had a lower appreciation of the engineering profession, lower confidence about their ability to succeed in engineering, and slightly more influences by family to study engineering than students who remained in the program [19]. Hence, those students who chose engineering majors and complete degree requirements were those who held positive perceptions towards engineering and had a measurable interest in science and technology [33].

Although most studies regarding persistence have not been based on engineering students, these studies suggest that non-cognitive variables should be considered as part of any model seeking to explain academic persistence.

Persistence of Underrepresented Groups in Engineering

The attrition of minority students in post secondary education represents a major obstacle in our country's need for a highly technical workforce. Due to the shifting demographics in the United States population and industry's projected need to draw from these growing groups, a large focus on the recruitment and retention of under-represented minorities in engineering has occurred [1, 34-41].

A report by the Congressional Commission on the Advancement of Women and Minorities in Science recommended greater focus on women and minorities, with these groups constituting more than two-thirds of the domestic workforce, yet greatly underrepresented in the science, engineering, and technology workforce [16, 35, 38, 42]. Recently the Bureau of Labor Statistics projected that the men's share of the labor force will decrease, with women increasing by 8.9% over the 2006-2016 period [43]. White, non-Hispanics will make up a decreasing share of the workforce, with Hispanics projected to account for an increasing portion, estimated at 16.4% with African Americans at 12.3% [43]. The same trend holds true for Texas with women and underrepresented minorities predicted to become an increasing resource, growing sustainably and diversifying Texas rapidly, from which both higher education and industry will draw students and employees [44]. According to population estimates, Texas recently tagged as a "majority-minority" state, has a minority population of 11.3 million, 50.2% of its total 22.5 million population [45, 46].

Historically, minority students have been underrepresented in higher education, particularly at four-year institutions. As a result of national efforts to increase diverse

participation in engineering, the enrollments of these groups have increased yet they still remain largely underrepresented among engineering degree attainment [34, 38, 47-49].

According to Seymour, only one-third of Hispanics and one-half of African Americans who enroll in science and engineering majors graduate in them [49]. In 2005, a study by the National Science Foundation indicated that the proportion of science and engineering degrees awarded to African Americans and Hispanics was 8% [24]. In comparison, the proportion of science and engineering degrees awarded to non-Hispanic Anglos was 65% [24]. This represents an 82% decrease from 1985-2005, reflecting both population changes and increasing college attendance by underrepresented groups. Nevertheless, relative graduation rates for minority students in engineering is about 50% that of non-minorities [17, 49]. Thus, the full impact of the gains that have been made in the enrollment of URM students in engineering has been overshadowed by low persistence rates.

To close the gap in the engineering degree attainment of minorities, an abundance of factors are believed to have influenced their persistence, ranging from the rigors of the engineering curriculum to the lack of family encouragement and support. Based on the literature, academic success in high school [50], involvement in campus life [32], and academic and social integration [12] increases the likelihood of African American students persisting in college. Specifically, attitudes and expectations with which students enter may vary and affect academic performance. In both the Hispanic and African American students, Brown and Clewell found evidence of low self-esteem and unfavorable perceived treatment by faculty [51].

This issue of gender has been widely studied regarding persistence in engineering. A recent national study profiling engineering students reported that “engineering differs from other majors most notably by a dearth of female students and a low rate of migration into the major [16].” This long time concern is increasing because, in this modern technology-oriented world, full use of human resources in science and engineering is a national economic imperative.

Over the years, many efforts in determining and increasing the persistence of women in engineering has taken place. The Women’s Movement raised consciousness so that women accepted engineering as a career choice. Currently, women comprise over 56% of the total U.S. workforce, however, they account for only 8.5% of the engineering profession [52]. When coupled with national reports indicating that since 1982, women have outnumbered men in undergraduate education, earning 58% of all bachelor’s degrees in 2005 alone [24, 53], the severe gender gap in engineering is apparent.

Studies and theories regarding gender and engineering persistence are numerous and diverse. Rosabeth Moss Katner’s theory of tokenism states that women’s persistence in undergraduate majors is proportionate to the gender balance in those majors and so the few women in science and engineering have the least persistence [54]. Surprisingly, data revealed that the strongest gender discrimination and pressure to quit occurs when the genders are balanced rather than when only a few women are involved [54].

One set of research efforts has focused extensively on self-confidence in relation to female student persistence in science and engineering [17, 28, 40, 55]. These studies report that gender differences in science and engineering major selection and persistence are closely related to women’s self-perceived ability to learn math and science.

Besterfield-Sacre et al. noted that at the end of their freshmen year, female engineering students maintained lower self-confidence in their basic engineering knowledge and skills, problem-solving abilities, and overall engineering abilities than male engineering students [33]. Declining self-confidence and self-efficacy in their science and engineering ability is what often leads to a switch into other fields [17, 33, 55].

A second set of studies has focused on academic prediction and attempts to distinguish potentially successful students from those who will leave the engineering field [17, 56]. In a 1994 benchmark study comparing students persisting in engineering undergraduate degree programs with those who chose to switch to another field of study, Seymour and Hewitt found that there were no real differences in high school preparation, ability, or efforts expended in their coursework [17]. Although these results were for both male and female undergraduates, they have been confirmed by other studies of female science and engineering undergraduates [28, 57].

Research suggests that female students are most concerned about academic self-confidence, isolation, gender bias, negative experiences in laboratory courses, classroom climate, poor advising, and lack of role models [15, 28, 55, 58]. Over the past 20 years, colleges and universities have developed numerous women in engineering programs to address these and other perceived problems.

Resilience Theory

History is repetitive with stories of survivorship, whether educational, racial or political, all having one thing in common – those who survived learned to be resilient. Rutter defined resilience as the “positive pole of the ubiquitous phenomenon of

individual differences in people's response to stress and adversity [59].” Masten, Best, and Garnezy referred to the theory of resilience as the “capacity for or outcome of successful adaptation despite challenging or threatening circumstances [60].” This two-dimensional construct is defined by the collections of exposure to adversity and the manifestation of positive adjustment in the face of adversity.

Over the past 25 years, modern research has taken the theory of resilience to a new level – deriving from diverse disciplines as health, developmental psychology and psychopathology [61-63]. Initially, researchers in each of these areas were attempting to identify the stressors in children or adolescents that led to outcomes such as poor health or social/academic factors. Few research studies could be found where the focus was on college students or adults. For example, the *Urban Monograph Series* on resilience includes a comprehensive annotated bibliography in which all of the 26 references are about children and adolescents [64]. Nevertheless, college is listed as a critical transition point [64, 65]. Critical transition points in education are defined as changes in each level of schooling (i.e. home to school, to elementary, to junior high, to high school, to college). At these critical transitions in their lives, when vulnerabilities are high, it is important to strengthen protective factors for students. This is the key factor in resilience theory [64].

Knowledge of factors associated with resilience has provided a basis from which to study what some have now termed, educational resilience; “the heightened likelihood of educational success despite personal vulnerabilities and adversities brought about by environmental conditions and experiences [61].” In the study of educational resilience, researchers identify and promote those factors that protect against the adverse effects

caused by an at-risk situation and that ultimately produce students who are academically successful. These factors have typically been categorized into personal and environmental factors [66-68].

Personal factors refer to the internal attributes and attitudes that the student uses to buffer the adverse effects of their situation or environment. Willingness to work hard, educational aspirations and motivation are a few of the personal factors believed to be associated with educational resilience [61, 68].

Environmental factors refer to the external influences that provide support and protect against negative factors threatening the resilient person. Positive adult contact, peer support and peer commitment to education are a few of the associated factors [65, 73].

The first year of college presents a challenge for many students. Protective facets that are in place during high school may change or cease to exist. For many students this adjustment alters their ability to cope, so they often withdraw from college [15]. The decision not to persist takes them to a new life trajectory where it becomes more difficult to attain social, monetary and career awards. Although there are many different factors that play into a students' decision to leave college, students that become socially and academically integrated are better able to cope with adversity [13] and therefore persist [14, 16].

Learning Styles

Learning styles research explains the ways individuals prefer to receive, process and present information and ideas. That preferred manner in which an individual understands, organizes and utilizes information in their learning environment is described as their learning style [69]. This style, developed over many years, is the natural combination of one's environmental, emotional, sociological, physiological and psychological makeup.

As a result of the increased interests placed on student persistence, leaning style theory and the critical role that its approach can play is gaining increased acceptance in the world of science and engineering. Several practitioners within the science and engineering domains have noted the importance of embedding a learning style approach with a variety of teaching strategies [70]. Assessing an individual's learning style is often seen as vital to the teaching and learning process. An effective match between the two may lead to improved student attitudes and higher student achievement [71]. There are a number of different assessment models and instruments available. Some models are multidimensional, encompassing cognitive, affective and psychological characteristics, and others are limited to a single variable, most frequently from the cognitive or psychological domain.

There is currently a need to identify individual learning styles as a basis for providing responsive instruction.

Working Definition

The evolution of the significance and validation of the term learning style has been long and complex. Generally speaking, it is used to describe the preferred manner in which an individual assimilates, organizes and utilizes information in their learning environment [69]. This style, developed over many years, is the natural combination of one's environmental, emotional, sociological, physiological and psychological makeup. Particularly, it is "... the way each learner begins to concentrate, process, and retain new and difficult information [72]."

Webster defines resiliency as "an occurrence of rebounding or springing back [73]." Although it has no universally accepted research-based meaning, the majority of the definitions used in literature are similar; that is, resilience is based on the realization that some people are more able to sustain themselves in adverse conditions and situations than others.

CHAPTER III

METHODOLOGY

The purpose of this study is to (1) explore relationship among dimensions of resilience theory and learning styles in engineering students and (ii) study how dimensions of both influence academic persistence in engineering. Data for this investigation were collected using two instruments: *The Index of Learning Styles* and the *Personal Resilience Questionnaire*. This chapter will discuss popular instruments in the fields of learning style and resilience theories, introduce the instruments used, describe the population studied, outline the research design, and discuss data collection procedures and statistical analysis methodologies employed in the study.

Instrumentation

Learning Styles

The theory of learning styles states that people preferentially take in and process information differently [70-72, 74-80]. Kolb, whose learning style instrument is credited by some as the first to be created in the United States, played a major role in initiating learning styles research.

In the last two decades, several models and measurement instruments have been developed to classify learning styles and identify individual preferences. Some are very generic and include a broad range of learning behaviors and dimensions. Other frameworks are more focused and highlight specific dimensions. Each instrument

measures different preferences, characteristics, or traits; has different degrees of reliability; and are used for different purposes.

Instruments available to assess a student's approach to learning include:

- Dunn and Dunn's Learning Style Model
- Learning Style Inventory
- Learning Style Questionnaire
- Myers-Briggs Indicator
- Curry's Onion Model
- Index of Learning Styles

Subsections below present a synopsis of each tool that includes a theoretical basis, instrument usage/population served, and the validity and reliability of its psychometric design. The section will conclude with selection of the instrument selected for this study.

Dunn and Dunn's Learning-Style Model

Rita and Kenneth Dunn began their work on learning styles in the 1960's in response to the New York State Education Department's concern for poorly achieving students. They believed that student's preferences and learning outcomes were related to factors other than intelligence, such as environment and taking parts in different types of activity [81, 82]. After examining accumulated research that repeatedly verified that there are individual differences in the way learners begin to concentrate on, process, absorb and retain new and different information, the Dunn's developed the VAK. The VAK measure three main sensory receivers: Visual, Auditory, and Kinesthetic to determine a dominant learning style. This approach is one of the most widely used

models of teaching today, developed for use across grade levels to improve the performance of all students, and in particular, low achieving students (reference). The model is based on two assumptions: it is possible to (1) identify individual student preferences for learning and (2) to use various instructional procedures and modify the instructional environment to match the preferences [82].

The Dunns' Learning-Style Model identifies 21 elements that affect each individual's learning and organizes them into 5 strands: individual's immediate environment, sociological preferences, physiological characteristics, and processing inclinations [81, 82]. Although Dunn and Dunn state strong claims of positive psychometric measures, some theorists argue that the model has poor validity [83]. With the validity being established by content and factor analysis, some feel that the Dunn's have misrepresented measurement, by complicating the results. Nevertheless, the Dunn's Learning Style Model has had widespread use with adult learners and has been utilized at more than 116 institutions of higher education [84]. However, its use in science and engineering education has been quite limited.

Learning Style Inventory

Kolb proposed a more specific model that focuses primarily on how individuals receive and process information. Kolb describes learning as a four-stage, cyclical process based on experimental learning theory [76, 85]. Kolb's four-stage learning cycle shows how experience is translated through reflection into concepts, which in turn are used as guides for active experimentation and the choice of new experiences. Kolb's

model offers both a way to understand individual people's different learning style, and also an explanation of a cycle of experimental learning that applies to us all [76].

The Learning Styles Inventory (LSI) was originally developed as part of an MIT curriculum development project that resulted in the first management textbook based on experimental learning [86]. The LSI measures four different information-perception orientations on the basis of a learner's preference of concrete experience over abstractness, and information-processing orientations on the basis of the learner's preference of action over reflection [76]. The varying orientations result in four types of learners: divergers, convergers, assimilators and accommodators.

Studies on validity of the LSI have criticized it for psychometric weaknesses, such as poor construct and face validity, low test-retest reliability, and lack of correlation between factors that should correlate with the classification of learning styles [87-89]. Despite the criticism, researchers continue to use the Kolb learning model under the premise that it provides some reference for analyzing a person's learning profile without recourse.

Learning Style Questionnaire

While accepting Kolb's learning style model, Honey and Mumford expressed dissatisfaction with the effectiveness of the inventory itself, stating poor face validity and questionable predictive accuracy [90]. This led them to develop an alternative instrument called the Learning Style Questionnaire (LSQ), which links the stages of the learning cycle with the four styles identifying whether one is predominantly an activist, a reflector, a theorist or a pragmatist [91]. The LSQ was designed to probe general

behavioral tendencies rather than learning styles, offering practical help in playing to one's strengths as learners or in developing as well rounded learners or both. Practical help follows from the belief of Honey and Mumford that, as preferences have been learned, they can be modified and improved upon.

Since its development, the LSQ has been translated into dozen of languages used throughout the world, in all sectors of commerce and education. Its most popular areas of use are in management training and development and at a number of colleges to raise student awareness of the way they learn and to develop their study skills [92].

Although the LSQ has attracted considerable interest, questions regarding its four-factor structure raised doubts as to the applicability of the instrument to students in general and business studies students, in particular [90]. Studies of the psychometric properties by Allinson and Hayes claimed that its temporal stability and internal consistency were well established and offered some evidence of construct validity but no of concurrent or predictive validity [93, 94]. It is not clear that the LSQ provides a satisfactory alternative to Kolb's inventory as a method of assessing learning styles [90, 94].

Myers-Briggs Indicator

Another model is the Myers-Briggs Indicator (MBTI), an instrument based on the concepts of Carl Jung [76, 80, 95]. Jung's theory states that the world can be perceived by either sensing or intuition and that people use their thinking or feeling to make decisions. Originally developed for use in the military, the MBTI assesses the relative strength of the four dichotomous processes of Extraversion versus Introversion

(EI), Sensing versus Intuition (SN), Thinking versus Feeling (TF), and Judging versus Perception (JP) [76].

The MBTI is a sixteen-type, forced choice self reported personality profile instrument. According to MBTI theory, each of the 16 personality types is considered qualitatively unique and represents a specific cluster of cognitive and affective preferences [80]. The results are then tabulated to indicate preferences for each of the four scales. Although a continuous scale score is provided for each dimension, the final personality profile contains a nominal score of preference. For example, a person who receives 12 items keyed for extroversion and 8 items for introversion is typed E, extroverted.

Over the past two decades the MBTI has been given to hundreds of thousands of people and the resulting profiles have been correlated with career preferences and aptitudes, management styles, learning styles and various behavioral tendencies. Unlike many other instruments, however, it requires a trained counselor to administer.

The validity of the MBTI is generally accepted as fairly sound. There has, however, been considerable debate about this because research on the factor analysis of the MBTI has not produced convincing results [96]. Dependent on each of the four scales, the test-retest reliability is noted as instable [97]. Although these patterns of limitations are consistent across various studies, this instrument continues to receive widespread use.

Index of Learning Styles

The Index of Learning Styles (ILS) is an instrument designed to assess preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global) of a learning style model formulated by Felder and Silverman. The ILS, first applied in the context of engineering education, categorizes students' preferences in terms of type and mode according to the four dimensions noted above. Felder states that learners with a strong preference for a specific learning style may have difficulties in learning if the teaching style does not match with their learning style [70]. It has been used to offer a basis for engineering instructors to devise teaching approaches that addresses the learning needs and contributes to the success of all students [78].

Each dimension consists of a dichotomy representing a way a person prefers to receive, process, and respond during a learning experience. The dichotomies in the dimensions do not exclude each other, they represent a continuum, that is, the student's preference can be strong, moderate or almost non-existent in one of the poles' dimensions and changes according to the time, the subject or the learning environment.

The first dimension distinguishes between an active and a reflective way of processing information. Active learners learn best by actively working and applying the learning material. In addition, they prefer working in groups where they can discuss the learned material. In contrast, reflective learners prefer to think about the material before trying to use it. Regarding communication, they prefer to work alone.

The second, sensing-intuitive dimension differentiates learners who prefer learning facts and concrete material and those who prefer to learn abstract material and discover new relationships on their own. Sensors like to solve problems with standard

approaches and are considered to be more realistic and sensible. In contrast, intuitive learners tend to be more innovative and creative, often becoming bored with memorization.

The third dimension covers visual versus verbal learners. This dimension differentiates learners who remember best and therefore prefer to learn from what they have seen, and learners who get more out of textual representations, regardless of whether they are written or spoken. Visual learners tend to find diagrams, sketches, photographs, or flowcharts or any other visual representation of course material to assist in learning. Verbal learners, on the other hand, write summaries or outlines of course materials in their own words, work in groups to have more effective learning experiences and gain understanding by hearing classmates' explanations.

In the fourth dimension, learners are portrayed according to their understanding. Sequential learners prefer learning in logical, linear steps. They tend to follow logical paths in finding solutions. In contrast, global learners use a holistic approach and learn in large leaps, often grasping the big picture. They tend to absorb learning material almost randomly without seeing connections but after they have learned enough material they suddenly get the whole picture.

The associated Index of Learning Styles (ILS) is a 44-item questionnaire that identifies learning styles according to the Felder-Silverman model. Each learner is characterized by a specific preference for each dimension. These preferences are expressed with values between +11 to -11 per dimension, with steps ± 2 . These ranges of values result from the 11 questions that are posed for each dimension. [78].

The ILS is an often used and well-investigated instrument to identify learning styles. Felder and Spurlin provided an overview of studies analyzing the response data of

the ILS regarding the distribution of preferences for each dimension as well as with verifying the reliability and validity of the instrument [78]. These studies supported the argument that the ILS is a reliable, valid and suitable psychometric tool.

Curry's Onion Model

Curry's Onion Model provides a well-established framework within which to view the main learning style theories [98]. Curry suggests that learning styles is a generic term under which three levels of learning behavior are considered: cognitive personality style, information processing style, and instructional preference [99]. Curry conceived the "onion model," with three levels of learning styles represented by a layer of an onion.

The outer layer of Curry's model examines instructional preference; an individual's choice of learning environment. This layer is considered to be the most observable, least stable, and most easily influenced. Considered to be the most observable, least stable and most easily influenced, this layer refers to different aspects of learning style, and those most influenced by external factors such as physiological and environmental stimuli associated with learning activities [100]. This layer parallels the main theory proposed by Dunn & Dunn, who believed that learning style reflects the manner in which elements of five stimuli affect an individual's ability to perceive, interact with and respond to the learning environment [74].

The middle layer concerns an individual's academic approach to processing information. This layer is considered to be more stable than the outer layer because it does not directly interact with the environment, although it is modifiable by learning strategies [101]. This layer includes Kolb's and Honey & Mumford's models of information processing.

The center of the model is comprised of measures of personality style, addressing an individual's approach to adapting and assimilating information, and is considered to be a permanent personality dimension [102]. This layer includes the Myers-Briggs Type Indicator with its dichotomous scales measuring an individual's personality profile.

Felder and Silverman drew explicit parallels between the active/reflective and sensing/intuitive dimensions and the Myers-Briggs extravert/introvert and sensing/intuitive dimensions, respectively. As such, the Index of Learning Styles overlaps the middle, information processing layer, and inner layer, cognitive personality layer and uses four dimensions to define an individual's learning style.

	Onion Model	Dunn and Dunn's Learning Style Model	Learning Style Inventory	Learning Style Questionnaire	Myers-Briggs Indicator	Index of Learning Styles
General	<ul style="list-style-type: none"> Provides overall framework for which to view main learning style theories. Three distinct levels of learning 	<ul style="list-style-type: none"> Based on instructional theory Addresses environmental preference for learning 	<ul style="list-style-type: none"> Based on information processing theory Encompasses preferred intellectual approach to assimilating information 	<ul style="list-style-type: none"> Based on information processing theory 	Based on personality learning theory	Based on information processing and cognitive personality theories
Design of the model	<ul style="list-style-type: none"> Three levels of learning examining instructional learning, information processing, and personality style Based on psychometric evidence and reviews of written documentation about learning style measures 	<ul style="list-style-type: none"> High/low preferences for 22 factors are identified by learners 	<ul style="list-style-type: none"> Based on the theory of experimental learning Designed to measure the strengths and weaknesses of a learner 	Alternative instrument to Kolb's model, with new terms for style preferences	<ul style="list-style-type: none"> Based on Jung's theory on four bipolar scales, producing 16 possible personality types Requires a trained counselor to administer 	<ul style="list-style-type: none"> Designed to capture the most important learning style differences among engineering students
Principal audience	Central goal was to observe the style differences among professional of different medical fields.	<ul style="list-style-type: none"> Adult learners in higher education Limited use in various branches of science and engineering 	Organizational Management	Business - Management training and development	<ul style="list-style-type: none"> Originally developed for use in the military 	<ul style="list-style-type: none"> Engineering education
Reliability	No evidence	Weight of evidence shows strong reliability	Weight of evidence shows low test-retest reliability	No evidence	Weight of evidence shows strong reliability	Weight of evidence shows strong reliability
Validity	No evidence	Weight of evidence shows poor validity	Weight of evidence shows poor construct and face validity	No evidence	Weight of evidence shows face validity is generally accepted	Weight of evidence shows strong validity
Implications for pedagogy		<ul style="list-style-type: none"> Individual differences in preferences can be discerned The stronger the preference, the more effects an intervention will have 	<ul style="list-style-type: none"> Provides a guide for the design and management of all learning experiences Assist learners to become competent in all four learning styles (concrete, abstract, active, and reflective) 	No evidence	The use of type in career preferences and aptitudes is widespread and has been used to steer students into suitable areas of study	Provide a basis for engineering instructors to formulate a teaching approach that addresses the learning of all students
Evidence of pedagogical impact		<ul style="list-style-type: none"> Isolation of individual elements in empirical studies allows for evaluation of the effects of those elements 	<ul style="list-style-type: none"> No evidence that correlation of learning styles improves academic performance in further education 		Limited evidence to suggest that matching teacher and learner types may increase student learning	Suitable tool to assess learning styles of individuals for the purpose of providing effective learning environments

Table 3.1 Summary of 6 major models of learning styles

Instrument Selection

This research looks to explore relationships among dimensions of learning styles in engineering students and study how factors influence persistence. The criteria most important in selecting an adequate instrument to assess student learning preferences in a college-level learning setting includes applicability to the engineering audience, ease in assessment, evaluates how an individual's processes, perceives and retains information, reliability and validity. An evaluation of these items is listed in Table 3.1.

Felder and Silver's *Index of Learning Styles* offers an investigation of an individual's learning preference on both an academic and cognitive approach. Research notes evidence that these two inventories represent important components regarding academic persistence [103]. This preference profile is concise and easy to administer with 44 short item questions, providing a choice between two responses for each question.

As an often used and well-investigated instrument, response data for the ILS have been collected in a number of studies. Weight of evidence concludes that the ILS is reliable and valid. Thus, the present study employed the ILS for assessing student learning styles based on the noted criteria.

Resilience Theory

Students at risk of academic failure often face an array of problems making it difficult for them to succeed in school. Consequently, one of the most compelling priorities on the national agenda is to close the achievement gap between those students who are academically successful and those who are at risk of failure. The basis of

resilience theory is the belief that every person can overcome adversity if important protective factors are present in that person or in their environment [104].

Resilience theory is a multifaceted field that has been addressed by social workers, psychologists, sociologists, educators and many others over the past few decades. In the context of education, one of the most widely used definitions of resilience is “the heightened likelihood of success in school and other life accomplishments despite environmental adversities brought about by early traits, conditions, and experiences [61].” The ability to thrive academically despite the presence of adverse conditions has important implications for the educational improvement of at risk students.

The concept of resilience has received increased attention over the years from researchers studying the amplified levels of stress experienced by college students. In college students, yielding to stress is characterized by damage to psychological functioning – such as symptoms of anxiety and depression – as well as physical functioning, such as signs and frequency of illness [105-108].

Assessment on resilience has been primarily through inductive study (e.g. using open-ended life histories) [109]. This approach has been suitable in enabling researchers to identify dynamics of resilience; however, measures devised to effectively assess resilience were few. Some instruments measured only one component of resilience. For example, the Ways of Coping Questionnaire measured coping, which is only one component of resilience [110]. For this investigation, instrumentation that measures all dynamics of resilience was needed.

The table on page 34 shows an overview of 3 instruments measuring resilience, the *Connor-Davidson Resilience Scale*, *Resilience Scale*, and the *Personal Resilience Questionnaire*, the populations for which they are appropriate, the reliability and validity of their instrumentation, and where they overlap and differ will be discussed. The instrument will be selected by evaluating the options with respect to the criteria required for this study.

Connor-Davidson Resilience Scale

The Connor-Davidson Resilience Scale (CD-RISC) was introduced in 2003 as a clinical measure to assess the positive effects of treatment for stress reactions, anxiety, and depression [111]. The CD-RISC is based on the authors' description of resilience as a multidimensional characteristic that varies with context, time, age, gender, and cultural origin, as well as within an individual subjected to different life circumstances [111]. Drawn from a number of sources, this self report scale is comprised of 25 items that includes concepts of control, commitment, challenge, goal-orientation, self-esteem, adaptability, social skills, humor, strengthening through stress and endurance of pain (Steinhardt). Respondents reply to this model using a 5-point Likert scale ranging from 0 (*not true at all*) to 4 (*true nearly all the time*). Total scores can range from 0 to 100, with higher scores reflecting greater resiliency.

Preliminary analyses of the CD-RISC in general population, primary care, psychiatric outpatient, and clinical trial samples support its internal consistency, test-retest reliability and validity. Connor and Davidson reported an internal consistency reliability coefficient of 0.89 and a test-retest reliability coefficient of 0.87. It is noted

that the scale exhibits validity relative to other measures of stress and hardiness and reflects different levels of resilience in populations that are thought to be differentiated by their degree of resilience [112].

Resilience Scale

The Resilience Scale (RS) was developed by Wagnild and Young based on a qualitative study of 24 elderly women who were judged to have successfully adapted to major life events. Intended to be applicable to other populations, including males and youth, this 25-item self-report questionnaire identifies five resilience themes: equanimity, meaningfulness, perseverance, existential aloneness and self-reliance [113].

The RS items are positively worded and responses are on a Likert scale ranging from 1 (agree) to 7 (disagree). The possible scores range from 25-175, and the higher the score, the higher the degree of resilience [114].

The internal consistency of the RS has been documented in a number of studies [115]. Descriptions of study participants' Cronbach alpha for the different studies were consistently high, ranging from 0.83 to 0.94 [114]. The test-retest reliability has been addressed in only a few studies. In one unpublished study, the test-retest coefficient was 0.67 at 1 month and 0.84 after 12 months, noting a need for further research to allow for final conclusion regarding test-retest reliability [115].

Construct validity was supported in various studies by correlations between the RS and measures of construct considered as theoretically linked to resilience. In 1993, Wagnild and Young demonstrated the concurrent validity of this scale by the

significantly correlating trait of resilience with adaptation indicators such as life satisfaction, morale, depression and physical health [115].

Personal Resilience Questionnaire

The Personal Resilience Questionnaire (PQR) was created by Darryl Conner in 1990 to study “how humans respond to major changes.” He established that the concept of resilience was vital to successfully implementing change and defined resilience as “the capacity to absorb high levels of change while displaying minimal dysfunctional behavior [116].” Individual scores on the PRQ represent a view of a person’s predilection and typical style when approaching new situations.

Conner’s questionnaire provides a method of assessing resilience while minimizing potential elements of bias. Written on a seventh grade reading level, students typically completed the PRQ in minimal time [117]. Responses show how much one agrees or disagrees with each item according to the six-item Likert-Type Response Scale.

Validity for the PRQ used a criterion-related approach. That is, a prediction is made about how the operationalization will perform based on a theory of construct. ORD showed the procedure of verifying the criterion-related validity of the PQR. In order to rest the predictive validity of the instrument for successful performance over change, ODR had to determine if there was a link among the PQR and change-related performance criteria [118]. Five studies were conducted to determine the predictive validity. The results suggested that there characteristics differentiate people from different groups.

Research on the reliability of the PQR used the Cronbach approach; internal consistency reliability coefficients were calculated for the seven sub-scales of the assessment instrument. Positive (world) has .80 of Cronbach's alpha, Positive (self) has 0.78, Focus has 0.78, Flexibility (thoughts) has 0.73, Flexibility (social) has 0.72, Organized has 0.69, and Proactive has 0.69 [119]. The Cronbach alpha coefficients indicate that the items making up each scale have a high level of covariance, indicating people tend to respond similarly to the various questions in each scale [119, 120].

Bryant tested the test-retest reliability of the PRQ, computing both among-person and within-person correlations. The among-person correlations assess the stability of each subscale, while within-person correlations reflect the stability of subscale rank-order over time [119]. He calculated the among-person correlations for each subscale of the PRQ over different time intervals (two, four, six and eight weeks), and found that the correlations fell between .71 and .80, which showed acceptable stability. From the statistical results, Bryant concluded "the among-person correlations... demonstrate the stability of the PRQ subscales over short to moderate time periods." He also found that the median within-person correlation for scores on the PRQ for two-week, four-week, six-week and eight-week periods were 0.91, 0.88, 0.88 and 0.79, respectively.

	Connor-Davidson Resilience Scale	Resilience Scale	Personal Resilience Questionnaire
General	<ul style="list-style-type: none"> Originally introduced as a clinical measure to assess the positive effects of treatment for stress reactions, anxiety and depression Identifies resilience as a multidimensional characteristic that varies with context, time, age, gender and cultural origin 	<ul style="list-style-type: none"> Based on the qualitative study of 24 elderly women who had adapted successfully after a major life event 	<ul style="list-style-type: none"> 70-item self-report measure of traits, skills and behaviors linked to resilient conduct Studies how individuals respond to major changes Provides a method of assessing resilience while minimizing potential elements of bias
Design of the model	<ul style="list-style-type: none"> Self-rated 25-item scale that measures the ability to cope with adversity Includes items corresponding to commitment, control, goal setting, patience and tolerance of negative affect Higher scores correspond to greater resilience 	<ul style="list-style-type: none"> 25-item self-reported scale identifying five elements of resilience: level-headedness, meaningfulness, perseverance, existential aloneness and self-reliance All items are positively worded Likert-type response scale 	<ul style="list-style-type: none"> Likert-type response scale Individual scores represents an individuals predilection and style when approaching new situations
Principal audience	Clinical		Originally designed for organizational management, college students
Reliability	Acceptable test-retest reliability	Poor test-retest reliability	Acceptable test-retest reliability
Validity	Acceptable claims of convergent and divergent validity	Weight of evidence show strong construct validity	Weight of evidence show strong criterion-related validity

Table 3.2 Summary of 3 major models of resilience theory

Instrument Selection

Based on resilience research, resilience can be both a predictor and outcome, depending on the theoretical focus. This study will evaluate both options as well as their influence on student persistence. Characteristics of interest will include appropriateness of instrument, ease of assessment, as well as evidence of reliability and validity.

Based on relevant descriptive and psychometric information regarding each instrument as shown in Table 3.2, the *Personal Resilience Question* was chosen as the

selected tool to perform this research. As previously defined, resilience is illustrated by the maintenance or improvement of social, occupational and/or personal performance following some change in circumstances. As a student adjusts to the college, the change of environment is only part of the equation. Students also have to adapt to new living conditions, social interactions and academic challenges. The subscales (dimensions) identified in the literature for resilience for students is the best assessed by the PRQ through its measures of skills, behaviors and dispositions. In addition, several research investigations by both external researchers and ODR were developed to determine the validity and reliability of the instrument [109, 121]. Research also indicated that the dimensions (subscales) described in the model are not independent of one another, but mutually reinforcing and self-enhancing with one another, so that each of them helps to facilitate the use of others [116].

Population

The population for this study was comprised of freshmen engineering students enrolled in the *Foundations of Engineering I* (ENGR 111) course at Texas A&M University the third month of the Fall semester, 2006 (The study was approved by Texas A&M's Institutional Review Board). ENGR 111 is based on engineering fundamentals and is designed to give a general overview of the engineering professions, ethics, and disciplines.

It is beneficial to understand the details of the freshmen engineering course in order to provide a context for this study. The students in this sample were calculus-ready and enrolled in the calculus series and calculus-based introductory physics which is a

course requirement. This Common body of Knowledge (CBK) course is required for all engineering majors before they can progress on to the second tier of the course and admission into an engineering department. Five sections of ENGR 111 were selected to participate. The classes were chosen to be as similar as possible and therefore honor sections were not included. There is nothing that suggests that the results of this study cannot be generalized to other engineering programs.

Student participation in the study was voluntary. Every student in each section was asked to sign the consent forms. The participants were those that signed and there were no reprisals for refusal to participate. In this letter, participants were also assured that their names would not appear in any of the results and the responses to the questionnaires would be kept confidential, only to be identified by number and used solely for the purposes of correlating data. The students were exposed to minimal risks.

Of the five sections evaluated, each section contained approximately 80 students, so the maximum possible sample was about 400 freshmen students. The number of students in each section varied based on the number present in class on the day of the assessment. The enrollment for each section was 64, 79, 84, 84 and 85. Complete response data was received from 220 students.

Administration of Survey

The engineering students in all five ENGR 111 sections were asked to complete both the personal resilience questionnaire and the index of learning styles November 2006. The on-line assessment, the Personal Resilience Questionnaire, was administered

first followed by the paper version of the Index of Learning Styles. This procedure was followed for each of the five sections.

A total of 220 paper and 327 on-line surveys were returned to the researcher, with the results of the on-line assessment delivered in SPSS format from the Conner Partners, developers of the Personal Resilience Questionnaire. The data were evaluated by quantitative research methods using the Statistical Package for the Social Sciences (SPSS) computer program. The survey instrument can be seen in Appendix B.

Statistical Analysis

Conner Partners, distributor of the ILS, initially processed the on-line surveys using SPSS for Windows. The results for each completed Index of Learning Styles survey were also entered into a data sheet within SPSS. Once the data was entered, factor analysis and multiple regression analysis were performed.

Factor analysis is a branch of multivariate analysis using covariance and correlation matrices to discover relationships among many variables (Adock 1954, Cattell 1952, Kim and Mueller 1978, Kline, P. 1994). The function of factor analysis is to uncover, in quantitative terms, the latent dimensions of a set of variables (Adock, 1954). Factor analysis is also used to simplify complex sets of data and to explain these variables in terms of their common underlying dimensions. In this study, factor analysis was used to validate whether or not the parameters are clustered according to the scales purposed by the creators of the Index of Learning Styles, identify relationships between the ILS and the PRQ, and to determine which parameters of the both tools have the greatest influence on persistence.

There are two types of factor analysis: exploratory and confirmatory. Exploratory factor analysis seeks to uncover the underlying structure of a large set of variables (Kim and Muller). Confirmatory factor analysis deals with specific expectations concerning the interrelationships of factors (Kim and Muller). There are three steps typically employed in a factor analysis, regardless of type. Those steps include preparing a covariance or correlation matrix, extracting initial factors and rotating to terminal solution.

Persistence was measured by looking at the freshmen engineering student's continued enrollment after their first semester. The persistence was then examined based on the student's assessment results of both tools yielding a result of 5 independent variables; where the dependent variable is academic persistence in engineering with binary variables values of 0 (did not persist) or 1 (persisted). To achieve this, the researcher used multiple logistic regression.

Multiple logistic regression is a flexible method of data analysis that may be appropriate whenever a quantitative variable is to be examined in relationship to any other factors. Multiple regression estimates the effect of multiple independent variables on a dependent variable. Relationships may be nonlinear, independent variables may be quantitative or qualitative, and one can examine the effects of a single variable or multiple variables with or without the effects of other variables taken into account.

SPSS for Windows was used to perform the regression analysis. Interpretations from the factor analysis, regression analysis will be presented in Chapter IV.

CHAPTER IV

PRESENTATION AND ANALYSIS OF DATA

The aim of this chapter is to present results from the data analyses performed in conjunction with this study. This chapter begins with a review of the study's results, and progresses through to analyzed data related to the research questions. The final section provides a summary of the results and transitions to the discussion in Chapter V.

Descriptive Parameters of Sample Respondents

Index of Learning Styles

The target population for this study was 398 students enrolled in the *Foundation of Engineering I* (ENGR 111) course at Texas A&M University. The researcher received 220 completed Index of Learning Styles assessments from the surveyed population, a response rate of 68.1%.

The descriptive analysis for gender showed 24.5% (n=54) of participants were female and 75.5% (n=166) were male. The higher concentration of male respondents is comparable to Texas A&M's College of Engineering undergraduate enrollment by gender (2006), 81.2% male and 18.8% female.

The descriptive analysis for ethnicity showed 80.4% (n=177) of participants were White, 11.4% (n=25) Hispanic, 5.5% (n=12) Asian American, and .91% (n=2) Black. No information regarding ethnicity was provided for 4 (1.82%) students. The higher response rate from the White population is comparable to Fall 2006 undergraduate

enrollees, 75% White (n=5,451), 12.6% (n=917) Hispanic, 4.9% (n=358) Asian American, and 2.7 (n=195) Black [122].

For this study, persistence is defined as those students who matriculated into the second year of the engineering program, Fall 2007. Descriptive analyses reveal a total of 169 (76.8%) students persisted. Of those, 72.2% (n=122) were male, 27.8% female (n=47) and 79.9% (n=177) White, 11.83% (n=20) Hispanic, 5.9% (n=10) Asian American, 0% Black, and 0.6% (n=1) American Indian.

Student Learning Styles

Felder and Silverman's Index of Learning Styles (ILS) was used to identify preferred learning styles of each participant. The seven measured dimensions include (A-R) Active-Reflective, (S-N) Sensing-Intuitive, (VS-VB) Visual-Verbal, and (SQ-G) Sequential-Global. Although dimensions of the ILS model are presented as dichotomous categories, Felder emphasizes these dimensions should not be treated as continua nor as either/or categories [79]. He argues that a student's preference on a dimension could be presented as mild, moderate or strong in either side [123]. For example, there is little difference among learners that prefer to learn in the mild-Active learning style mode versus those in mild-Reflective mode. Therefore, the percentages for the mild, moderate, and strong ranges of each learning style dimension were combined for frequency data analysis of this study.

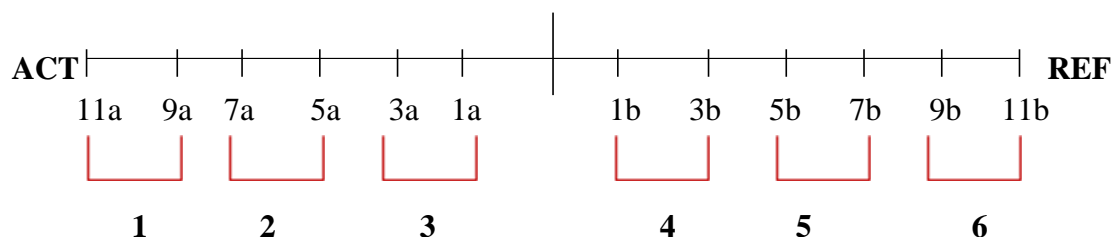


Figure 4.1 Recoded dimensions of the Index of Learning Styles

The analysis report consists of scores on a scale of 1 to 11 (odd numbers only) for one dichotomy of each of the four dimensions of the ILS. A score of 1 to 3 in either dichotomy of a dimension indicates a learning style preference that is fairly balanced. A score of 5 to 7 indicates a moderate preference and a score of 9 to 11 indicates a very strong preference in the associated dichotomy of the dimension. Raw data for the ILS were combined based on the mild, moderate and strong ranges for each learning style dimension, as shown in Figure 4.1. For example, for the Active-Reflective dimension, a raw score of 11a – 9a was re-coded as 1, representing a strong Active preference. A score of 2 reflected a raw score of 7a – 5a (moderate Active), 3 (3a – 1a, balanced Active), 4 (1b – 3b, balanced Reflective), 5 (5b – 7b, moderate Reflective), and 6 (9b – 11b, strong Reflective). Results of the instrument were keyed into SPSS and statistical evaluations were conducted to compare percentages of preferred learning styles of the student sample populations.

The average learning styles for the sample population are 3.11 for Active-Reflective, 3.08 for Sensing-Intuitive, 2.19 for Visual-Verbal, and 3.26 for Sequential-Global. The majority of the students were in the balanced/moderate range for each dimension except Visual-Verbal, where students showed a balanced Visual preference.

The results for the Active-Reflective dimension reported whether participants preferred either “active” or “reflective” learning styles. As shown in Figure 4.1, 55.5% of participants ranged between the mild-Active (BALANCEACT) (30%) and mild-Reflective (BALANCEREF) range (25.5%). These participants were relatively balanced between their preference for the Active and Reflective learning style dimensions. Twenty-three percent (n=51) of the participants reported they preferred to learn in moderate-Active (MODERATEACT) range while 8.6% (n=19) of the participants preferred to learn in moderate-Reflective (MODERATEREF) range. The data showed that very few participants, 12.6% (n=28), preferred to learn in the strong-Active (STRONGACT) and strong-Reflective (STRONGREF) ranges. As indicated in Figure 4.2, over 50% of participants favored a balanced Active-Reflective learning preference, revealing a normal distribution.

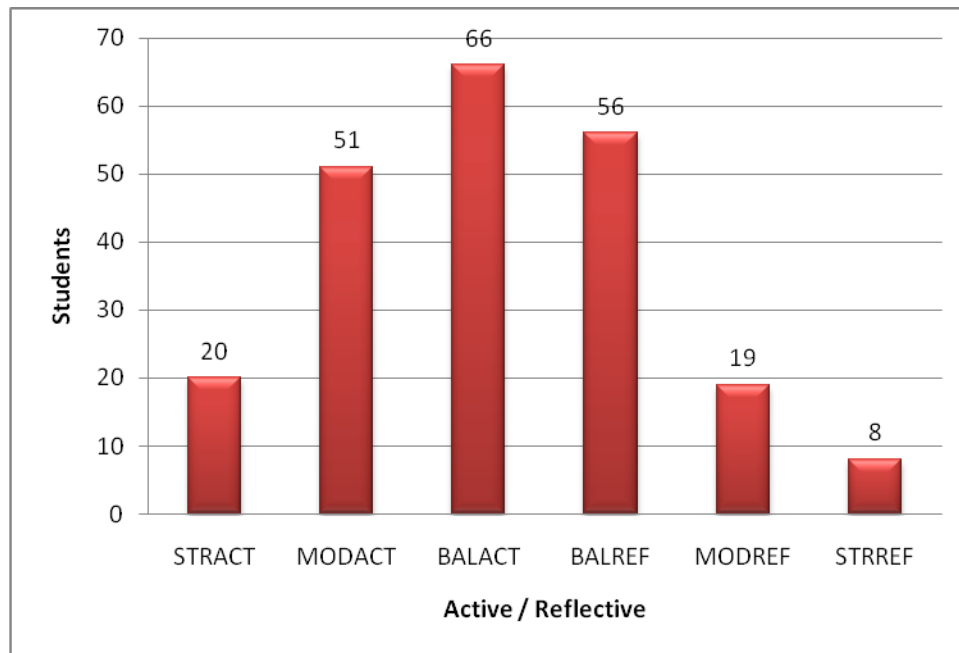


Figure 4.2 Frequency values for active-reflective style dimension

Figure 4.3 shows the highest concentrations of learners (49.6%, $n=109$) were relatively balanced between their preference for the Sensing (BALANCESNS) (27.3%) and Intuitive (BALANCEINT) (22.3%) learning style dimensions. Twenty-six percent ($n=56$) of participants reported they preferred to learn in moderate-Sensing (MODERATESNS) range while 7% ($n=15$) preferred to learn in moderate-Intuitive (MODERATEINT) range. Furthermore, 11% ($n=25$) of participants preferred to learn in strong-Sensing (STRONGSNS) range and 6.8% ($n=15$) of participants preferred to learn in strong-Intuitive (STRONGINT) range.

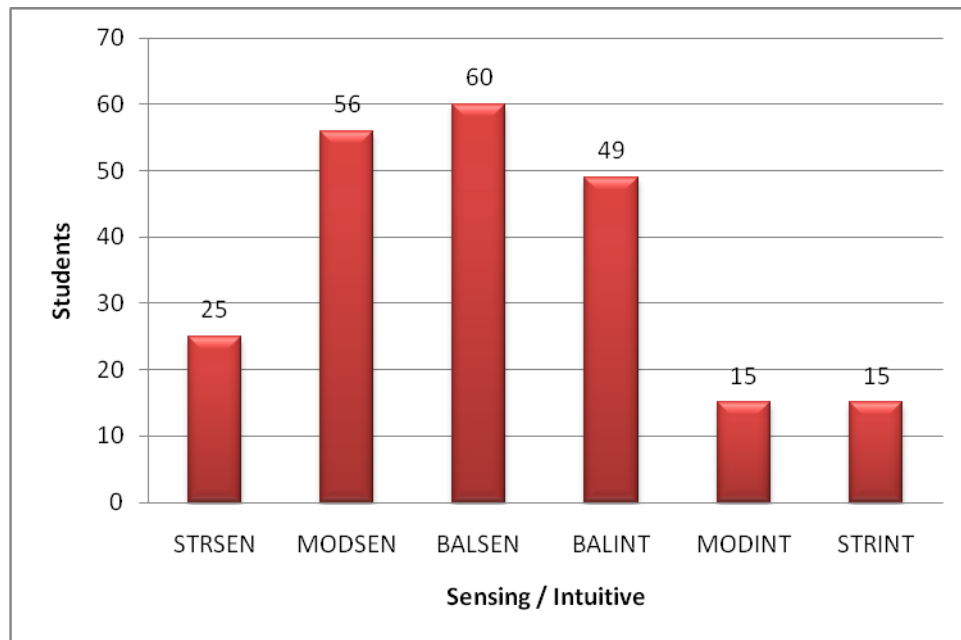


Figure 4.3 Frequency values for sensing-intuitive style dimension

Figure 4.4 shows the highest concentration of learners (55.4%, $n=122$) were relatively balanced between their preference for Visual (BALANCEVIS) (20.9%) and Verbal (BALANCEVRB) (34.5%) learning style dimensions. Thirty-two percent ($n=70$) of learners reported they preferred to learn in moderate-Visual range while 9% ($n=20$) of participants preferred to learn in moderate-Verbal (MODERATEVRB) range. However, data showed only 4% ($n=8$) of participants ranged between the moderate-Visual (MODERATEVIS) (2.7%) and moderate-Verbal (MODERATEVRB) (0.9%) ranges.

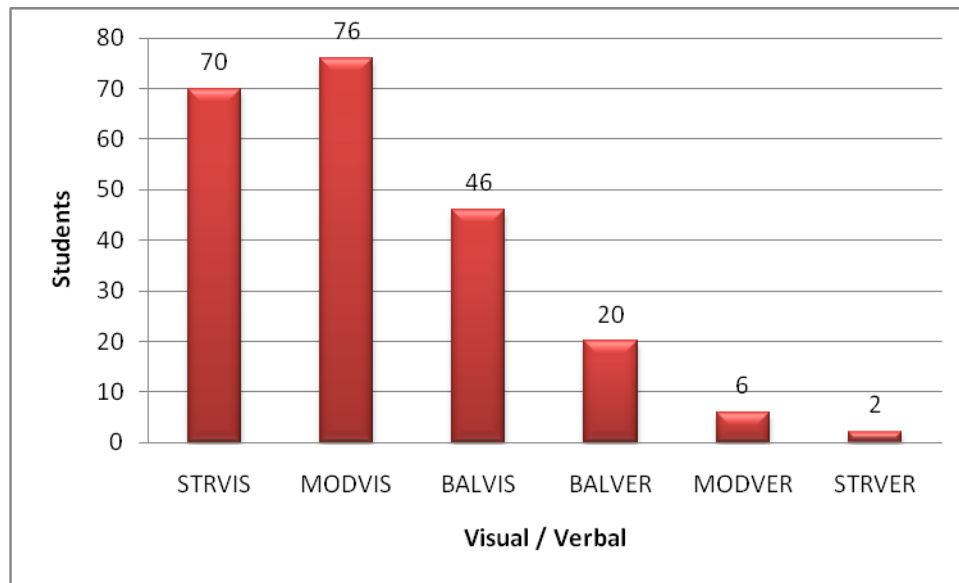


Figure 4.4 Frequency values for visual-verbal style dimension

Figure 4.5 shows the highest concentrations of learners were relatively balanced between their preference for Sequential (BALANCESEQ) (36.4%) and Global (BALANCEGLO) (n=55) learning style dimensions. Furthermore, data reveals 61% (n=135) of participants preferred to learn in Sequential mode. Data shows 21.4% (n=47) of participants reported a preference for the moderate-Sequential (MODERATESEQ) range, while 10.9% (n=24) of participants preferred to learn in moderate-Global (MODERATEGLO) range. Additionally, statistics showed only 6.3% (n=14) of participants ranged between strong-Sequential (STRONGSEQ) (3.6%) and strong-Global (STRONGGLO) (2.7%) ranges.

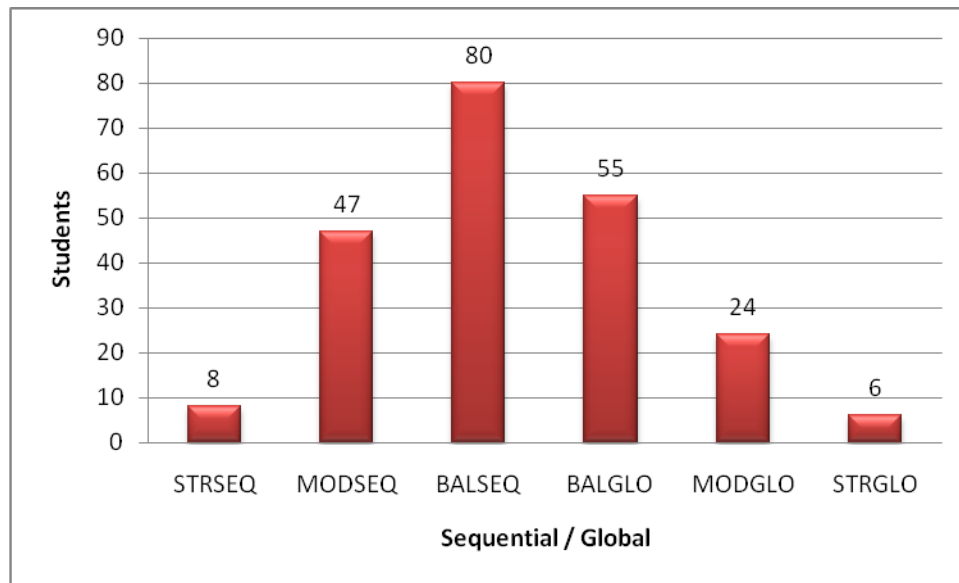


Figure 4.5 Frequency values for sequential-global style dimension

Personal Resilience Questionnaire

The target population of this study included 398 students enrolled in the *Foundation of Engineering I* (ENGR 111) course at Texas A&M University. A total of 319 completed surveys were returned from the surveyed population, a response rate of 80.2%.

The gender distribution heavily favors men, 78.1% (n=250) versus 21.6% (n=69) for women. No information regarding gender was provided for 1 (0.3%) student. The gender distribution is representative of Texas A&M University's College of Engineering Fall 2006 undergraduate enrollment by gender, 18.8% female and 81.2% male [122].

The descriptive analyses showed 67.1% (n=214) of participants were White, 9.7% (n=31) Hispanic, 4.7% (n=15) Asian American, and .94% (n=3) Black. The ethnicity distribution is comparable to Fall 2006 undergraduate enrollees in the College of Engineering at Texas A&M University.

As previously noted, persistence is defined as those students who matriculated into the second year of the engineering program, Fall 2007. Descriptive analyses show a total of 237 (74.3%) students persisted. No information was reported for 4 (1.7%) students. Of those, 76.4% (n=181) were male and 23.6% female (n=56).

Student Resilience

The *Personal Resilience Questionnaire (PRQ)* was used to measure resilience characteristics of the study population, determine relationships among resilience characteristics, and student persistence problem areas. The PRQ measured seven dimensions of resilience: positive (yourself), positive (world), focused, flexible (thoughts), flexible (social), organized and proactive. Resilience questionnaire items used a 6-point Likert-type scale: 1 (*strongly disagree*), 2 (*disagree*), 3 (*slightly disagree*), 4 (*slightly agree*), 5 (*agree*), and 6 (*strongly agree*). Tabular details of resiliency indicators of the study population are presented in Figure 4.6.

For any characteristic, a score that is extremely high relative to other scores represents a strength but also a tendency to overuse the characteristic and under-use the remaining characteristics when facing change. Results reveal the study population was relatively high in the “positive (world)” construct.

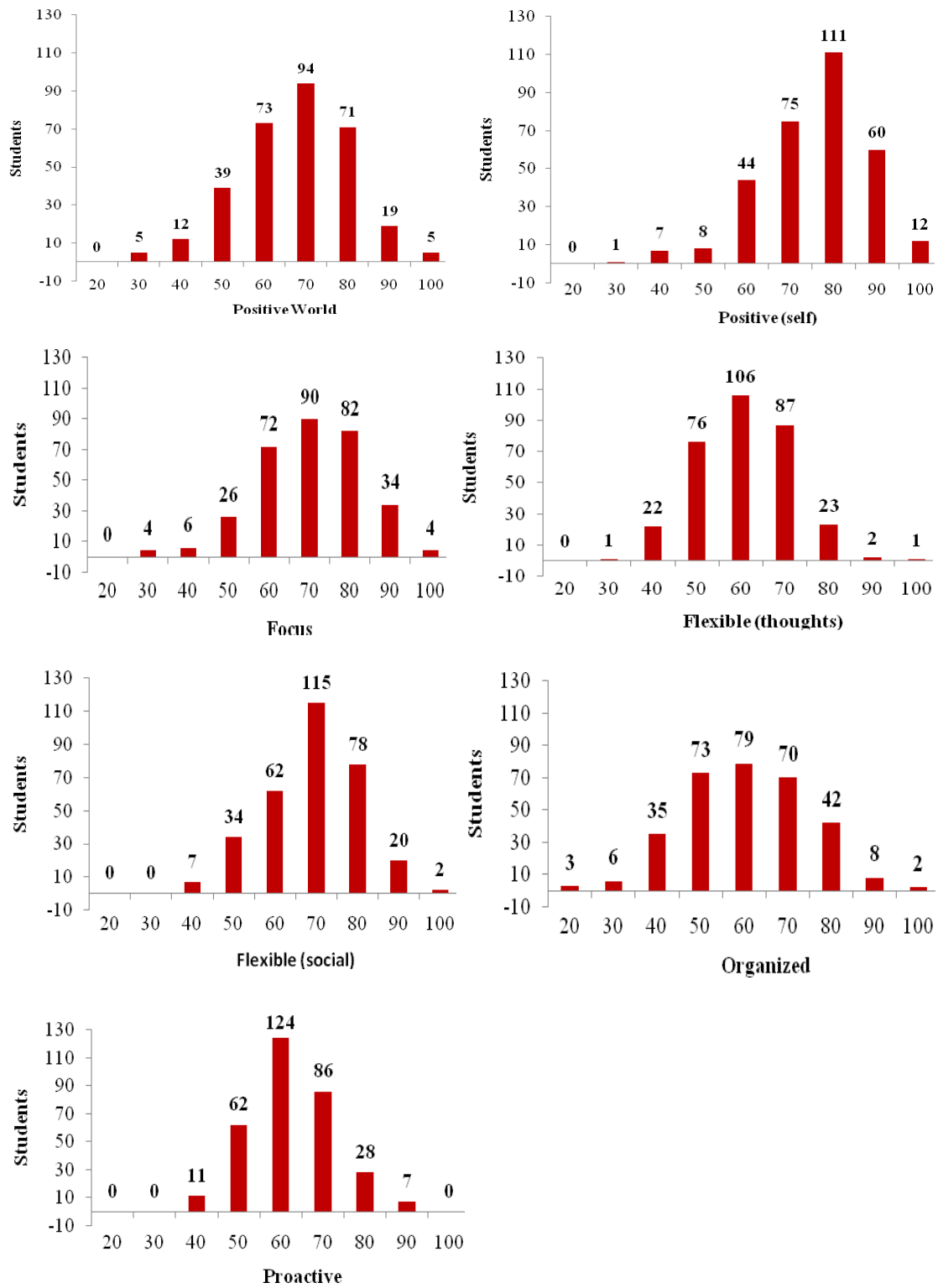


Figure 4.6 Frequency details for resilience indicators

Results of Data Analysis

To determine the relationships between elements of learning style, resilience and persistence a number of evaluations were performed. This section presents the results of the three analyses: multiple regression analysis, factor analysis and multivariate general linear model.

Regression Analysis

Index of Learning Styles

Student persistence was selected as the dependent variable for this study. The four dimensions of learning styles, seven dimensions of resilience, and eleven dimensions of both learning styles and resilience were independent variables. The general purpose of utilizing multiple regression models is to learn about relationships between elements of learning styles and persistence, resilience and persistence, and combined relationships of learning styles and resilience with student persistence in engineering.

Following the aforementioned trend, learning style dimensions were combined to represent mild, moderate, and strong learning style preferences. A score of 1 indicated a strong preference in the active, sensing, visual and sequential dimensions. A score of 2 indicated a moderate preference and a score of 3 indicated a balanced preference. A score of 4 indicated a balance preference for reflective, intuition, verbal or global. A score of 5 indicated a moderate preference and a score of 6 indicated a strong preference.

Correlations for learning styles and student persistence were performed using the most familiar measure of dependence between two quantities, the Pearson Correlations. This bivariate correlation measures the strength of linear relationships between two variables, varying from -1 to +1, with 0 indicating no relationship (random pairing of values) and 1 indicating perfect relationship. Table 4.1 summarizes the Pearson Correlations for the four dimensions of learning styles: active-reflective, sensing-intuitive, visual-verbal, and sequential-global. The abbreviations used are ACT_REF, SNS_INT, VIS_VBR, and SEQ_GLO. The table reveals a significant relationship ($p = .035$) between student persistence and the Sequential-Global ($r = -.122$) learning style dimension. We can conclude that in order to persist, it would favor a student to have a balance sequential resilience characteristic.

		Persistence	ACT_REF	SNS_INT	VIS_VBR	SEQ_GLO
Pearson Correlation	Persistence	1.000	.051	-.047	.007	-.122
	ACT_REF	.051	1.000	.016	.191	.092
	SNS_INT	-.047	.016	1.000	.047	.279
	VIS_VBR	.007	.191	.047	1.000	-.140
	SEQ_GLO	-.122	.092	.279	-.140	1.000
Sig. (1-tailed)	Persistence	.	.225	.246	.458	.035
	ACT_REF	.225	.	.404	.002	.086
	SNS_INT	.246	.404	.	.244	.000
	VIS_VBR	.458	.002	.244	.	.019
	SEQ_GLO	.035	.086	.000	.019	.

Table 4.1 Correlations for learning styles and student persistence (n=220)

Table 4.2 contains the correlation coefficient and coefficient of determination for the *Index of Learning Styles*. This summary provides information about the regression line's ability to account for total variation in the dependent variable. The R-value represents the multiple correlations of independent variables with the dependent variable. In this analysis $R = .140$, indicating an insignificant relationship between the independent and dependent variables. The R^2 value determines how much of the variation in one variable is due to the other variable. The R^2 value is .020; revealing 2% of the variation in student persistence is determined by learning styles. It, too, is insignificant.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.140 ^a	.020	.001	.423

a. Predictors: (Constant), SEQ_GLO_RC, ACT_REF_RC, VIS_VBR_RC, SNS_INT_RC

Table 4.2 Model summary for Index of Learning Styles

Table 4.3 presents the results of a specific general linear model (GLM), an extension of the linear modeling process for a single dependent variable. GLM allows models to fit data that follows probability distributions other than the normal distribution. It relaxes the requirement of equality or constancy of variances that is required for hypothesis tests in traditional linear models.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	25.477 ^a	151	.169	.837	.814
Intercept	36.593	1	36.593	181.631	.000
ACT_REF_RC	.957	5	.191	.950	.455
SNS_INT_RC	.713	5	.143	.708	.620
VIS_VBR_RC	1.417	5	.283	1.407	.233
SEQ_GLO_RC	.499	5	.100	.495	.779
ACT_REF_RC * SNS_INT_RC	1.459	13	.112	.557	.879
ACT_REF_RC * VIS_VBR_RC	1.149	8	.144	.713	.679
ACT_REF_RC * SEQ_GLO_RC	1.909	10	.191	.947	.497
SNS_INT_RC * VIS_VBR_RC	3.242	12	.270	1.341	.217
SNS_INT_RC * SEQ_GLO_RC	4.378	15	.292	1.449	.151
VIS_VBR_RC * SEQ_GLO_RC	2.111	9	.235	1.164	.332
ACT_REF_RC * SNS_INT_RC * VIS_VBR_RC	.052	4	.013	.065	.992
ACT_REF_RC * SNS_INT_RC * SEQ_GLO_RC	.305	2	.153	.758	.473
ACT_REF_RC * VIS_VBR_RC * SEQ_GLO_RC	.302	2	.151	.750	.476
SNS_INT_RC * VIS_VBR_RC * SEQ_GLO_RC	.000	0	.	.	.
ACT_REF_RC * SNS_INT_RC * VIS_VBR_RC * SEQ_GLO_RC	.000	0	.	.	.
Error	13.700	68	.201		
Total	169.000	220			
Corrected Total	39.177	219			

a. R Squared = .650 (Adjusted R Squared = -.126)

Table 4.3 General Linear Model (GLM) for Index of Learning Styles

The standardized coefficient Beta, β , an indicator of slope, also confirms the lack of relationship between elements of learning styles and student persistence. Beta is

calculated by rescaling the unstandardized B. The β value allows results to be compared with other β coefficients and used in other statistical analyses.

The β values for this analysis are as follows: active-reflective, $\beta = .068$, sensing-intuitive, $\beta = -.011$, visual-verbal, $\beta = -.023$, and sequential-global, $\beta = -.129$. Beta values indicate low relationships between constructs of learning styles and student persistence. As indicated in Table 4.4, there is no significant relationships present; yet, there is evidence that the sequential-global ($p=.074$) dimension may offer some insight.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	.886	.130		6.830	.000
ACT_REF_RC	.023	.024	.068	.976	.330
SNS_INT_RC	-.003	.022	-.011	-.152	.880
VIS_VBR_RC	-.009	.026	-.023	-.334	.739
SEQ_GLO_RC	-.049	.027	-.129	-1.795	.074

a. Dependent Variable: Persist_Fall07

Table 4.4 Regression coefficients for Index of Learning Styles

In the absence of assuming a linear relationship, an ANOVA was conducted to further investigate relationships between the sequential-global learning style construct and student persistence. There was an insignificant effect between Sequential-Global and student persistence, $F = 1.201$, $p = 0.31$. Results of this analysis are shown in Table 4.5.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.070 ^a	5	.214	1.201	.310
Intercept	54.621	1	54.621	306.735	.000
SEQ_GLO_RC	1.070	5	.214	1.201	.310
Error	38.108	214	.178		
Total	169.000	220			
Corrected Total	39.177	219			

a. R Squared = .027 (Adjusted R Squared = .005)

Table 4.5 ANOVA for sequential-global learning style dimension

Personal Resilience Questionnaire

Table 4.6 summarizes the Pearson Correlations for student persistence and 7 dimensions of resilience: positive (world), positive (self), focus, flexibility (thoughts), flexibility (social), organized, and proactive. The abbreviations optimism, esteem, focus, cogflex, social, organize, and proactive are used, respectively. From Table 4.6 we can conclude significant relationships between resilience dimensions positive (self) ($p = .043$) and focus ($p = .003$) and student persistence.

		Persistence	Optimism	Esteem	Focus	Cogflex	Social	Organize	Proactive
Pearson Correlation	Persistence	1.000	.058	.097	.155	-.049	-.037	.067	-.054
	Optimism	.058	1.000	.659	.540	.309	.543	.259	.346
	Esteem	.097	.659	1.000	.785	.343	.413	.414	.327
	Focus	.155	.540	.785	1.000	.198	.368	.503	.275
	Cogflex	-.049	.309	.343	.198	1.000	.300	-.182	.552
	Social	-.037	.543	.413	.368	.300	1.000	.115	.396
	Organize	.067	.259	.414	.503	-.182	.115	1.000	-.032
	Proactive	-.054	.346	.327	.275	.552	.396	-.032	1.000
Sig. (1-tailed)	Persistence	.	.153	.043	.003	.196	.258	.118	.171
	Optimism	.153	.	.000	.000	.000	.000	.000	.000
	Esteem	.043	.000	.	.000	.000	.000	.000	.000
	Focus	.003	.000	.000	.	.000	.000	.000	.000
	Cogflex	.196	.000	.000	.000	.	.000	.001	.000
	Social	.258	.000	.000	.000	.000	.	.021	.000
	Organize	.118	.000	.000	.000	.001	.021	.	.284
	Proactive	.171	.000	.000	.000	.000	.000	.284	.

Table 4.6 Correlations for resilience and student persistence (n=314)

Table 4.7 contains the correlation coefficient and coefficient of determination for the *Personal Resilience Questionnaire*. In this analysis, $R = .207$, indicating an insignificant relationship between elements of resilience and student persistence. The R squared value equals .021 and it, too, is insignificant.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.207 ^a	.043	.021	.426

a. Predictors: (Constant), Proactive, Organize, Social, Cogflex, Optimism, Focus, Esteem

b. Dependent Variable: Persistence

Table 4.7 Model summary for *Personal Resilience Questionnaire*

In the absence of assuming a linear relationship, an ANOVA was performed.

Contrary to linear results, Table 4.8 reveals no significant relationships present between dimensions of the PRQ and student persistence.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	39.510 ^a	212	.186	1.012	.481
Intercept	6.074	1	6.074	32.967	.000
Optimism	4.456	32	.139	.756	.815
Esteem	6.899	28	.246	1.337	.149
Focus	5.160	27	.191	1.037	.429
Cogflex	3.270	25	.131	.710	.836
Social	6.033	27	.223	1.213	.243
Organize	5.770	32	.180	.979	.510
Proactive	4.117	25	.165	.894	.612
Error	18.608	101	.184		
Total	237.000	314			
Corrected Total	58.118	313			

a. R Squared = .680 (Adjusted R Squared = .008)

Table 4.8 ANOVA for the *Personal Resilience Questionnaire*

The β values for this analysis are as follows: optimism, $\beta = .046$, esteem $\beta = -.015$, focus, $\beta = .232$, cogflex, $\beta = -.049$, social, $\beta = -.093$, organize, $\beta = -.055$, and proactive, $\beta = -.066$. Table 4.9 reveals a significant relationship between resilience construct focus ($p=.016$) and student persistence.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	.786	.200		3.926	.000
Optimism	.001	.003	.046	.564	.573
Esteem	.000	.004	-.015	-.147	.883
Focus	.008	.003	.232	2.416	.016
Cogflex	-.002	.003	-.049	-.668	.505
Social	-.003	.003	-.093	-1.345	.179
Organize	-.002	.002	-.055	-.797	.426
Proactive	-.003	.003	-.066	-.938	.349

a. Dependent Variable: Persistence

Table 4.9 Regression coefficients for Personal Resilience Questionnaire

To further investigate the relationship between student persistence and resilience constructs positive (self) and focus, an ANOVA was conducted. There were no significant main effects for positive (self) and focus.

Index of Learning Styles and the Personal Resilience Questionnaire

Table 4.10 summarizes the Person Correlations for student persistence and the 11 combined dimensions of learning styles and resilience: active-reflective, sensing-intuitive, visual-verbal, sequential-global, positive (world), positive (self), focus, flexibility (thoughts), flexibility (social), organized, and proactive. The abbreviations used are ACT_REF, SNS_INT, VIS_VBR, SEQ_GLO, Optimism, Esteem, Focus, Cogflex, Social, Organize, and Proactive. From Table 4.10 we can conclude significant relationships between student persistence and resilience elements positive (world), positive (self), focus and organized.

		Persistence	Optimism	Esteem	Focus	CogFlex	Social	Organized	Proactive	ACT_REF_RC	SNS_IN_TRC	VIS_VB_RRC	SEQ_GLO_RC
Pearson Correlation	Persistence	1	0.134	0.19	0.206	-0.03	-0.027	0.124	0.042	0.008	-0.01	0.034	-0.149
	Optimism	0.134	1	0.646	0.492	0.312	0.593	0.161	0.313	-0.268	0.012	-0.102	-0.082
	Esteem	0.19	0.646	1	0.773	0.267	0.414	0.377	0.237	-0.039	-0.091	0.011	-0.054
	Focus	0.206	0.492	0.773	1	0.109	0.331	0.466	0.174	-0.008	-0.197	-0.005	-0.088
	CogFlex	-0.03	0.312	0.267	0.109	1	0.311	-0.252	0.533	-0.122	0.514	-0.097	0.263
	Social	-0.027	0.593	0.414	0.331	0.311	1	0.065	0.332	-0.376	0.028	0.006	-0.006
	Organized	0.124	0.161	0.377	0.466	-0.252	0.065	1	-0.12	0.032	-0.214	0.092	-0.222
	Proactive	0.042	0.313	0.237	0.174	0.533	0.332	-0.12	1	-0.132	0.422	-0.027	0.098
	ACT_REF_RC	0.008	-0.268	-0.039	-0.008	-0.122	-0.376	0.032	-0.132	1	0.02	0.23	0.022
	SNS_INT_RC	-0.01	0.012	-0.091	-0.197	0.514	0.028	-0.214	0.422	0.02	1	0.042	0.299
	VIS_VBR_RC	0.034	-0.102	0.011	-0.005	-0.097	0.006	0.092	-0.027	0.23	0.042	1	-0.132
	SEQ_GLO_RC	-0.149	-0.082	-0.054	-0.088	0.263	-0.006	-0.222	0.098	0.022	0.299	-0.132	1
Sig. (1-tailed)	Persistence	.	0.037	0.005	0.003	0.346	0.358	0.049	0.287	0.46	0.449	0.328	0.023
	Optimism	0.037	.	0	0	0	0	0.016	0	0	0.435	0.087	0.139
	Esteem	0.005	0	.	0	0	0	0	0.001	0.304	0.113	0.439	0.238
	Focus	0.003	0	0	.	0.074	0	0	0.01	0.456	0.004	0.471	0.121
	CogFlex	0.346	0	0	0.074	.	0	0	0	0.052	0	0.097	0
	Social	0.358	0	0	0	0	.	0.193	0	0	0.353	0.467	0.466
	Organized	0.049	0.016	0	0	0	0.193	.	0.054	0.337	0.002	0.11	0.001
	Proactive	0.287	0	0.001	0.01	0	0	0.054	.	0.039	0	0.36	0.096
	ACT_REF_RC	0.46	0	0.304	0.456	0.052	0	0.337	0.039	.	0.397	0.001	0.384
	SNS_INT_RC	0.449	0.435	0.113	0.004	0	0.353	0.002	0	0.397	.	0.29	0
	VIS_VBR_RC	0.328	0.087	0.439	0.471	0.097	0.467	0.11	0.36	0.001	0.29	.	0.039

Table 4.10 Correlations for learning styles, resilience and student persistence (n=179)

Table 4.11 contains the correlation coefficient and coefficient of determination for the model summary of *Index of Learning Styles* and *Personal Resilience Questionnaire*. In this analysis, $R = .303$ indicating an insignificant relationship between the independent and dependent variables. The R squared value is .092 and it, too, is insignificant.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.303 ^a	.092	.032	.411

a. Predictors: (Constant), Proactive, Organize, Social, Cogflex, Optimism, Focus, Esteem, SEQ_GLO_RC, VIS_VBR_RC, SNS_INT_RC, ACT_REF_RC

b. Dependent Variable: Persistence

Table 4.11 Model summary for Index of Learning Styles and Personal Resilience Questionnaire

The β values for this analysis are as follows: active-reflective, $\beta = -.014$, sensing-intuitive, $\beta = .032$, visual-verbal, $\beta = .009$, sequential-global, $\beta = -.051$, optimism, $\beta = .003$, esteem $\beta = -.003$, focus, $\beta = .005$, cogflex, $\beta = -.003$, social, $\beta = -.006$, organize, $\beta = .000$, and proactive, $\beta = .001$. Table 4.12 reveals no significant relationships between the combined learning style and resilience constructs and student persistence. There is evidence, however, that the resilience element flexibility (social) ($p=.072$) may be a useful predictor.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	0.665	0.314		2.116	0.036
Optimism	0.003	0.004	0.097	0.853	0.395
Esteem	0.003	0.005	0.103	0.745	0.457
Focus	0.005	0.004	0.162	1.3	0.195
CogFlex	-0.003	0.004	-0.092	-0.866	0.388
Social	-0.006	0.004	-0.18	-1.808	0.072
Organized	0	0.003	-0.022	-0.245	0.807
Proactive	0.001	0.004	0.029	0.311	0.756
ACT_REF_RC	-0.014	0.029	-0.04	-0.479	0.632
SNS_INT_RC	0.032	0.03	0.105	1.082	0.281
VIS_VBR_RC	0.009	0.029	0.025	0.322	0.748
SEQ_GLO_RC	-0.051	0.031	-0.134	-1.658	0.099

Table 4.12 Regression coefficients for Index of Learning Styles and Personal Resilience Questionnaire

To further investigate the relationship between flexibility (social), positive (world), positive (self) and focus when the combined elements of resilience and learning styles are evaluated against student persistence, an ANOVA was conducted. Table 4.13 shows significant main effects for flexibility (social) ($F = 1.652$, $p = .051$), positive (self) ($F = 1.765$, $p = .037$), and focus ($F = 1.899$, $p = .021$).

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	22.136 ^a	110	.201	1.533	.029
Intercept	12.851	1	12.851	97.909	.000
Social	5.637	26	.217	1.652	.051
Optimism	4.857	29	.167	1.276	.204
Esteem	5.329	23	.232	1.765	.037
Focus	5.983	24	.249	1.899	.021
Error	8.925	68	.131		
Total	139.000	179			
Corrected Total	31.061	178			

a. R Squared = .713 (Adjusted R Squared = .248)

Table 4.13 ANOVA for Flexibility (social), Positive (world), Positive (self), and Focus with combined constructs of Index of Learning Styles and Personal Resilience Questionnaire

Factor Analysis

Chapter III presented background information on factor analysis and summarized the extraction and rotation methods. Three extraction methods were considered: maximum likelihood, least square and principal component analysis.

In this study, the principal components analysis method was adopted over maximum likelihood and least squares methods, as both methods produced one or more communalities greater than 1. This indicated an improper/invalid solution to be interpreted with caution.

Three methods were examined to determine the number of factors used in the factor analysis. Those methods include eigenvalue criterion, Scree tests, and interpretability.

The eigenvalue represents total variance explained by each factor. Factors with an eigenvalue greater than 1 may be considered for extraction from the analysis. Based on the eigenvalue criterion, four (4) factors should be extracted from the analysis.

The Scree test is a graphical representation of eigenvalues. It identifies the place where the smooth decrease of eigenvalues appears to level off right of the plot [124]. The rule when using the Scree Test suggests that factors prior to the point where the eigenvalues level off to form a straight line with a horizontal slope are usually close enough to zero that they can be ignored. This analysis suggests three (3) factors should be extracted from the analysis. Figure 4.7 displays the Scree plot for the performed analysis.

Both tests yielded a different number of factors for extraction. The eigenvalue criterion indicated 4 factors and the Scree Test indicated 3 factors. Due to the inconsistency in the results, the interpretability criterion was used. The interpretability criterion suggests that final judgment should rest with the researcher based on rational inference and scientific knowledge. It was decided that 4 factors would be used.

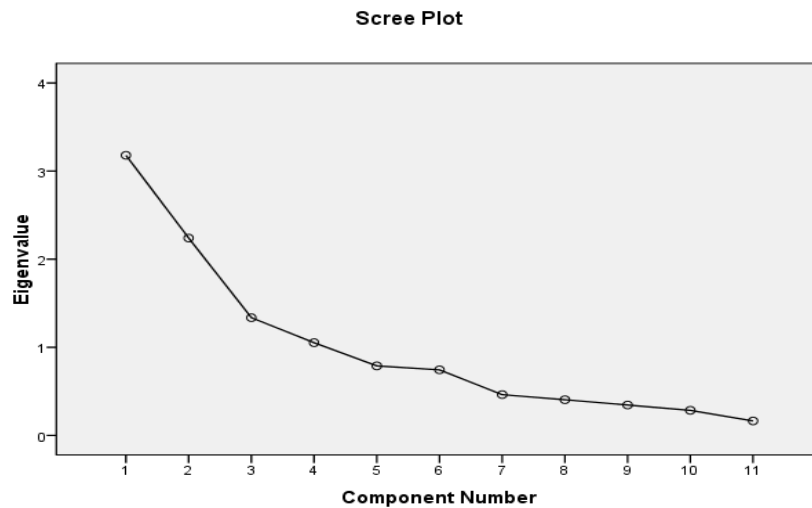


Figure 4.7 Scree plot

To determine loading of each variable on one of the extracted factors while minimizing loading on all other factors, the rotation method was used. The exact choice of rotation depends largely on assumption of whether or not relation between the underlying factors exists. In this case, the oblique approach was used. The oblique rotation assumes the factors are related to one another. Specifically, the direct oblimin (oblique) was used.

Factor analyses were performed on the combined 11 constructs using the aforementioned settings. When principle component analyses are used as the extraction method, results are referred to as components versus factors. The extracted components accounted for 70.9% of the variance, judged to be satisfactory.

The final step in factor analysis, prior to interpretation, was review of the pattern matrix chart to determine significance of factor/component loadings. According to Spearman's Theory, "factor loadings are the correlation of the variables with the factor [component] [125]." Mathematically, they are weighted combinations of variables which

best explain variance. Factor loadings are presented similar to correlations, with values between ± 1 . The interpretation of positive or negative signs depends on the rotation type. In the case of an oblique rotation, a negative sign suggests a negative correlation.

Significance of factor loadings is determined by establishing a cut-off and comparing the loadings of components with the scales. A review of literature reveals a wide cut-off range, 0.2 to 0.7. Kline suggests factor loadings greater than 0.3 be regarded as significant or salient [125]. Salient indicates that a relationship exists between the variable and the factor [component] [126]. Comrey and Lee suggests no item loads $< .3$ should be considered because less than 9% of the item's variance is accounted for [127]. For sample sizes of 100, with a minimum significant correlation coefficient ($p < .05$), loadings of 0.3 – 0.4 and higher should be determined significant [126].

For this study, $n=139$, significance between the scale and component was determined by values greater than or equal to 0.45. Table 4.14 displays the linear combination of the variables and pattern matrix generated for this study. The matrix of regression-type weights is reflective of the unique effect each factor contributes to a given observed variable.

	Component			
	1	2	3	4
Optimism	.580	.232	-.431	-.034
Esteem	.916	.156	.026	-.010
Focus	.921	-.022	.055	-.079
CogFlex	.119	.785	-.126	-.110
Social	.303	.191	-.664	.129
Organized	.630	-.362	.104	.093
Proactive	.150	.703	-.233	.161
ACT_REF_RC	.236	.053	.853	.206
SNS_INT_RC	-.206	.816	.117	.105
VIS_VBR_RC	-.047	.124	.173	.915
SEQ_GLO_RC	.014	.508	.322	-.430

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 11 iterations.

Table 4.14 Pattern matrix from factor analysis

Table 4.15 provides a synopsis of the pattern matrix showing significant components and scale loadings. Values are rounded to two decimal places. Table 4.16 shows the scale grouping based on the factor analysis.

	Component			
	1	2	3	4
Optimism	0.58			
Esteem	0.92			
Focus	0.92			
CogFlex		0.79		
Social			-0.66	
Organized	0.63			
Proactive		0.70		
ACT_REF_RC			0.85	
SNS_INT_RC		0.82		
VIS_VBR_RC				0.92
SEQ_GLO_RC		0.51		-0.43

Table 4.15 Component loadings

Component 1	Component 2	Component 3	Component 4
Positive (world)	Flexibility (thought)	Flexibility (social)	Visual - Verbal
Positive (self)	Proactive	Active - Reflective	Sequential - Global
Focus	Sensing - Intuitive		
Organized	Sequential - Global		

Table 4.16 Scaled groupings based on factor analysis

Upon examination, scaled groupings for component 1 relate to positive personal characteristics and motivations such as self-efficacy or self-referent thought and the ability to mentally sequence events. This component is representative of those with strong sense of goals and priorities, and ability to apply structure.

Component 2 groupings relate to cognitive factors and the way one prepares for possible consequences. This includes one's ability and willingness to look at situations from multiple points of view and suspend judgment while considering alternative perspectives.

Component 3 groupings relate to one's approach to received information and how it is shared with others. This includes recognition of when one's own resource capacity is overdrawn and he or she needs to draw on resources of others.

Component 4 relates to the way one progresses towards understanding. This includes the way one may best receive information and how they "get" the information being learned.

New derived groupings were renamed to represent components 1 through 4: Walton's self-efficacy, cognitive ability, resourceful, understanding. The interpretation of component loadings concludes the factor analysis. Using the newly established groupings, means were computed for each category and regression analysis was performed.

Regression Analysis (on groupings)

A useful byproduct of factor analysis is factor scores. Factor scores are composite measures computed for each subject on each factor. Factor scores were computed for each factor and used as predictor variables in a multiple regression analysis. Multiple regression analysis was used to determine the unique role of each grouping in predicting student persistence. This enables identification of the best predictors to be focused on in future actions.

Regression based factor scores were computed. These scores predict the location of each individual on the factor or component. The main advantage of the regression based method is that it maximizes validity [128]. This means the procedure provides highest correlations between a factor score and the corresponding factor.

Persistence was selected as the dependent variable. Walton's self-efficacy, cognitive ability, resourceful, and understanding were selected as independent variables. Groupings were used to determine if there is any difference in the relationship with the derived groupings and persistence and the actual groupings and persistence.

Table 4.17 summarizes the Pearson Correlations for the derived groupings. From this table we can conclude that there is a significant relationship between student persistence and Walton's self-Efficacy.

		Persistence	Walton's Self Efficacy	Cognitive Ability	Resourceful	Understanding
Pearson Correlation	Persistence	1.000	.197	-.041	-.023	.085
	Walton's Self-Efficacy	.197	1.000	.016	-.265	.110
	Cognitive Ability	-.041	.016	1.000	-.109	-.105
	Resource	-.023	-.265	-.109	1.000	.000
	Understanding	.085	.110	-.105	.000	1.000
Sig. (1-tailed)	Persistence	.	.004	.291	.379	.128
	Self-Efficacy	.004	.	.413	.000	.071
	Cognitive Ability	.291	.413	.	.072	.080
	Resource	.379	.000	.072	.	.496
	Understanding	.128	.071	.080	.496	.

Table 4.17 Correlations for derived groupings

Table 4.18 contains the correlation coefficient and the coefficient of determination for the model summary of the derived groupings. The R value equals .045

indicating an insignificant relationship between the dependent and the independent variables. The R squared value is .023 and it, too, is insignificant.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.212 ^a	.045	.023	.413

a. Predictors: (Constant), Understanding, Resource, Cognitive Ability, Self-Efficacy

Table 4.18 Model summary for derived groupings

The coefficients computed in the regression analysis are shown in Table 4.19. The unstandardized coefficients, B, are Walton's self-efficacy, .084, cognitive ability, -.015, resourceful, 0.10 and understanding, .026. This reveals a slight relationship between Walton's self-efficacy, resourceful, and understanding with student persistence. Additionally, the values reveal a negative relationship between student persistence and cognitive ability.

The standardized coefficient Beta, β , an indicator of slope, reveals low relationships between the independent and dependent variables. There is statistical significance present in Walton's self-efficacy ($\beta = .198$, $p = .019$) and no significance present in the other independent variables.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.787	.031		25.324	.000
	Walton's Self_Efficacy	.084	.033	.198	2.555	.011
	Cognitive_Ability	-.015	.032	-.036	-.476	.635
	Resourceful	.010	.031	.025	.328	.743
	Understanding	.026	.032	.060	.800	.425

a. Dependent Variable: Persistence

Table 4.19 Regression coefficients for derived groupings

Discussion of Major Findings

Student Persistence and Learning Style Indicators

The researcher's analysis of relationships between student persistence and four indicators of learning styles yielded one significant correlation. The sequential/global construct ($r = -.122$) revealed a negative association with student persistence. This implies that both high and low sequential/global learners are associated with both students who persist and students that do not persist in engineering. This relationship is indication that a student's approach to absorbing information is similar, whether a student persists or not. We can conclude that in order to persist, it would favor a student to have a balanced sequential-global resilience characteristic.

Student Persistence and Resilience Indicators

The researcher's analysis of the relationship between student persistence and seven indicators of resilience yielded two significant correlations. However, the positive (self) ($r = .097$, $p = .003$) and focus ($r = .155$, $p = .003$) constructs revealed a small correlations with student persistence. Small correlations imply a change in the positive (self) or focus construct is not correlated with changes in student persistence. Further analysis employed use of standardized coefficients, β , which also confirms the focus construct ($\beta = 2.416$, $p = .016$) as a significant predictor of student persistence. The researcher interpreted this significant relationship as those students who persisted in engineering had resilient characteristics based on the indicator "focus." This is an indicator of how well an individual has defined and clearly understands his or her goals or objectives. Furthermore, it describes a person's commitment to goals and ability to maintain direction in confusing situations. Previous studies show students with higher scores of "focus" had strong sense of direction and set priorities [117].

Student Persistence, Learning Styles and Resilience Indicators

The researcher's analysis of relationships between student persistence and combined constructs of learning styles and resilience yielded four significant results. Resilience indicators, positive (world) ($r = .037$), positive (self) ($r = .005$), focus ($r = .003$), and organized ($r = .049$), revealed small correlations with student persistence. Further analysis employed use of standardized coefficients and coefficient of determination, both yielding insignificant relationships. Evidence revealed the construct flexibility (social) ($r = .072$) to be a useful predictor. In the absence of a linear

relationship, an ANOVA was performed on resilience constructs flexibility (social), positive (world), positive (self), and focus. Significant relationships were yielded for flexibility (social) ($r = .051$), positive (self) ($r = .037$) and focus ($r = .021$). The researcher interpreted the significant results as students who persist in engineering possess characteristics of being good team players, high self-esteem, and ability to set goals and prioritize actions.

Student Persistence and Derived Groupings

Factor analysis was performed on constructs of learning styles and resilience. Factor analysis resulted in four newly derived groupings, Walton's self-efficacy, cognitive ability, resourceful, and understanding. Analysis of the relationship among student persistence and derived groupings yielded one significant relationship. New component, self-efficacy ($r = .004$), revealed a small correlation to student persistence. Further analysis employed use of coefficients of determination, yielding insignificant relationships. Use of standardized coefficients further supported a significant relationship between student persistence and Walton's self-efficacy ($p = .019$). Walton's self-efficacy represents the combined groupings of resilience characteristics positive (world), positive (self), focus, and organized. The researcher interpreted the significant results as students who persist in engineering possess characteristics of ability to set goals, high self-esteem, risk aversion, and building structure in chaos.

CHAPTER V

SUMMARY AND CONCLUSIONS

The purpose of this study was to assess the relationship among dimensions of resiliency theory and learning styles in engineering students and study how dimensions of both influence academic persistence in engineering. This final chapter contains a brief overview of the study, followed by a discussion of results, implications, limitations, and recommendations for future research. This discussion provides potential explanations or interpretation of findings and suggests implications that may impact audiences of concern.

Overview

The researcher examined the relationship among four indicators of learning styles and seven indicators of resilience of first year engineering students at Texas A&M University. Quantitative data collection methods were used to fulfill the objectives of the study. Quantitative data for this study was collected using two instruments: *Index of Learning Styles (ILS)* and the *Personal Resilience Questionnaire (PRQ)*. The ILS was designed to assess preferences for learning on four dimensions. The PRQ was designed to assess how individuals respond to major changes.

Using data from the collected instruments, multiple regression analyses was performed to determine strong or meaningful relationships among constructs of resilience, learning styles and academic persistence. For further investigation in the absence of assuming of linear relationships, the researcher employed analysis of

variance (ANOVA) procedures. The results of the analyses confirmed the presence of one significant construct, Sequential-Global, with the ILS and two significant constructs (Positive (self) and Focus) with the PRQ.

Factor analysis was performed to discover similar concepts among learning styles and resilience. The results of the factor analysis confirmed the presence of four latent factors/components. The four components represent the new derived groupings. Regression analysis was performed on the results of the factor analysis to understand the functional relationship between the independent and dependent variables. Specifically, the coefficients of the regression analysis showed a significant relationship between student persistence and self-efficacy.

Interpretation of Findings

The findings of this study supported the viewpoint students that persist possess preferences for learning favoring some learning abilities over others [70]. The analyses of learning style data suggested there were different learning style preferences represented within the population of this study, with a significant negative relationship between the sequential/global construct and student persistence. The negative correlation indicates that a student with strong sequential/global characteristics will have few problems persisting in engineering. With the exception of weak-visual and the weak-verbal learning style modes, data indicated the majority of participants preferred learning style modes that were balanced for each learning style dimension. Felder and Silverman suggest that learners who prefer balanced learning style modes are adaptive to differing learning environments. As a result, the majority of participants in this study were

flexible in their ability to learn within opposing learning style modes for each dimension of the *Index of Learning Styles*. I don't believe that the ILS should be used to predict academic performance or draw inferences about what students are and are not capable of doing. Learning styles reflect preferences and tendencies, and can therefore provide individual insight into one's learning strengths and weaknesses that can be measured against indicators showing a strong relationship with student persistence.

Another significant finding revealed resilience indicators positive (self) and focus were important predictors of academic persistence. The premise of self-efficacy as a predictor of student persistence was also evidenced in the analysis of the new derived component. This supports a common theme of previous research concerning self-efficacy and the academic achievement of college students [129-134]. Lent, and et al. also reported that self-efficacy was a good predictor of grade point average [135]. These students not only achieved higher grades, but were more likely to persist in engineering majors than those with low self-efficacy [136]. This is a key finding in that it emphasizes the importance of enhancing motivation and achievement for engineering students. That is contrary to the literature that describes undergraduate engineering programs as cutthroat, competitive, and inattentive to students' needs, particularly during the first 2 years [137, 138]. In many engineering programs, students perceive faculty members as too busy to be helpful or antagonistic toward their questions and concerns [17]. As a result, this may communicate to the student that they are not important or appreciated, which can threaten their self-esteem.

The results of both assessment tools were measured against student persistence. Significant findings revealed three predictors of student persistence, flexibility (social),

positive (world), and focus. The results of this analysis are clear: team work, prioritization, and confidence are key factors regarding persistence in engineering. These findings support Austin's theory of student development, the amount of physical and psychological energy that a student devote to the academic and social aspects of college life [32].

Implications

The results of this study support the position that there are linkages between resilience, learning styles and student persistence in engineering. The information gleaned from this study has implications for institutions of higher education, students, faculty, and staff. The information is particularly important for research-intensive institutions who serve a large population of undergraduate engineers. Strengthening support systems and eliminating barriers may be the most effective ways to encourage students to persist in efforts to achieve their career goals [139].

The empowerment of students individually, in groups, and through personal mentoring may be of great value. Enhancing self-efficacy should be a focus of all individuals involved with education. As with goals and academic performance, situations are best when one's perceived self-efficacy is in line with one's true capabilities [140]. Student perceptions that they cannot perform, when in actuality they are capable of achievement, inhibits personal growth and experience. Bandura's research has demonstrated that persons with high perceived self-efficacy demonstrated the following characteristics: set more challenging goals and performance standards, persist longer in pursuit of goals, and more venturesome in their behavior, recover quickly from

setbacks and frustrations, and experience less fear, anxiety, stress, and depression [130]. These characteristics can be taught, mentored, and examined in students admitted to the college of engineering in an effort to increase retention and graduation. Tinto stated, “the more frequent and rewarding interactions are between students and other members of the institutions, the more likely students are to stay [13].”

Limitations of the Study

As with any endeavor, there are factors outside of our control that impact results obtained. This section discusses the limitations experiences in this study, which may limit the broad application of these results.

1. Although there is nothing that suggests the results cannot be generalized to other engineering programs, it is critical to point out that the relatively small sample utilized in this study was drawn from a large state institution.
2. Student participants volunteered, therefore, results obtained may not be applicable to students where participation is mandated.
3. No external measure was used to corroborate the results of this study. Results are based on self-reported responses.
4. Length of both assessment tools is lengthy, at best. The ILS consists of 44-questioned instrument that takes about 15 minutes to complete. The PRQ consists of 75 scales and takes approximately 25 minutes to complete.

Recommendations for Future Research

Based on the findings of this study, the following are both recommendations to improve student persistence in engineering as well as additional areas for research. The following recommendations are being made based on the findings of this study.

1. Additional research is need with different populations to confirm the findings based on the association of learning styles, resilience and student persistence in engineering.
2. In order to gain a deeper understanding of the complex construct of resiliency, research that includes a qualitative component would be advantageous. In addition to analyzing the data from a quantitative perspective, subjects who scored extremely high or low on the Personal Resilience Questionnaire could be interviewed for the purpose of clarifying and/or verifying their levels of resilience and student persistence. The combination of the quantitative and qualitative approach could augment the research in this area.
3. The exploration of the use of other instruments or tools could provide another dimension of relationship between learning styles, resilience and student persistence.
4. Additional research is needed to explore balanced course instruction and to assist students in understanding their learning strengths and areas for improvement.

REFERENCES

- [1] National Academy of Sciences, *Rising above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future*, Washington, DC: National Academy Press, 2005.
- [2] National Science Board, *Science and Engineering Indicators 2006*, Arlington, VA: National Science Foundation, 2006.
- [3] Hernandez, J., and M.A. Lopez, "Leaking Pipeline: Issues Impacting Latino/a College Student Retention," *Journal of College Student Retention: Research Theory and Practice*, Vol. 6, No. 1, 2004, pp. 37-60.
- [4] Jackson, S.A., "Ahead of the Curve: Future Shifts in Higher Education," *EDUCAUSE Review*, Vol. 39, No. 1, 2004, pp. 10-18.
- [5] Chubin, D.E., and W. Pearson, Jr. (Eds.), *Scientists and Engineering for the New Millennium: Renewing the Human Resource*, Washington, DC: Commission on Professionals in Science and Engineering, 2001.
- [6] National Science Board, *Science and Engineering Indicators 2002*, Arlington, VA: National Science Foundation, 2002.
- [7] Yokomoto, C.F., M.E. Rizkalla, C.L. O'Loughlin, M.A. El-Sharkawy, and N.P. Lamm, "Developing a Motivational Freshman Course Using the Principle of Attached Learning," *Journal of Engineering Education*, Vol. 88, No. 1, 1999, pp. 99-106.
- [8] MacGuire, S., and G. Haplin, "Factors Related to Persistence in Engineering: Results of a Qualitative Study," Paper presented at the Annual Meeting of the Mid-South Educational Research Association Conference, Auburn, AL, 1995.
- [9] Astin, A.W., *Four Critical Years*, San Francisco, CA: Jossey-Bass, 1977.
- [10] Choy, S.P., *Access & Persistence: Findings from 10 Years of Longitudinal Research on Students. Informed Practice: Syntheses of Higher Education Research for Campus Leaders*, Washington, DC: American Council on Education, 2002.
- [11] Lang, M., "Student Retention in Higher Education: Some Conceptual and Programmatic Perspectives," *Journal of College Student Retention*, Vol. 3, No. 3, 2001, pp. 217-229.

- [12] Tinto, V., "Stages of Student Departure: Reflections on the Longitudinal Character of Student Leaving," *Journal of Higher Education*, Vol. 59, No. 4, 1988, pp. 438-455.
- [13] Tinto, V., *Leaving College: Rethinking the Causes and Cures of Student Attrition*, Chicago, IL: University Chicago Press, 1993.
- [14] Pell Institute for the Study of Opportunity in Higher Education, *Student Retention and Graduation: Facing the Truth, Living with the Consequences*, Washington, DC: Pell Institute for the Study of Opportunity in Higher Education, 2004.
- [15] Felder, R., K.D. Forrest, L. Baker-Ward, E.J. Dietz, and P. Mohr, "A Longitudinal Study of Engineering Student Performance and Retention: I. Success and Failure in the Introductory Course," *Journal of Engineering Education*, Vol. 82, No. 1, 1993, pp. 15-21.
- [16] Ohland, M., S.D. Sheppard, G. Lichtenstein, O. Eris, D. Chachara, and R. Layton, "Persistence, Engagement, and Migration in Engineering Programs," *Journal of Engineering Education*, Vol. 97, No. 3, 2008, pp. 259-278.
- [17] Seymour, E., and N. Hewitt, *Talking about Leaving: Why Undergraduates Leave the Sciences*, Boulder, CO: Westview Press, 2000.
- [18] Beaufait, F.W., "Engineering Education Needs Surgery," *Proceedings, 21st Annual Frontiers in Education Conference*, 1991, pp. 519-522.
- [19] Besterfield-Sacre, M., C.J. Atman, and L.J. Shuman, "Characteristics of Freshmen Engineering Students: Models for Determining Student Attrition in Engineering," *Journal of Engineering Education*, Vol. 86, No. 2, 1997, pp. 139-149.
- [20] French, B., J.C. Immekus, and W.C. Oakes, "An Examination of Indicators of Engineering Students' Success and Persistence," *Journal of Engineering Education*, Vol. 94, No. 4, 2005, pp. 419-425.
- [21] Tinto, V., "Colleges as Communities: Taking Research on Student Persistence Seriously," *The Review of Higher Education*, Vol. 21, No. 2, 1998, pp. 167-177.
- [22] Astin, A.W., "Engineering Outcomes," *ASEE Prism*, Vol. 3, No. 1, 1993, pp. 27-30.
- [23] Engineering Workforce Commission, *Engineering and Technology Degrees, 2007*, Elkridge, MD: Engineering Workforce Commission, 2008.

- [24] National Science Board, *Science and Engineering Indicators 2008*, Arlington, VA: National Science Foundation, 2008.
- [25] Hewitt, N., and E. Seymour, "A Long, Discouraging Climb," *ASEE Prism*, Vol. 1, No. 6, 1991, pp. 24-28.
- [26] Jenkins, M., and R.G. Keim, "Gender Trends in Engineering Retention," *Proceedings, 34th Annual Frontiers in Education Conference*, Vol. 3, 2004, pp. 13-18.
- [27] Ohland, M., G. Zhang, B. Thorndyke, and T. Anderson, "Grade-Point Average, Changes of Major, and Majors Selected by Students Leaving Engineering," *Proceedings, 34th Annual Frontiers in Education Conference*, Vol. 1, 2004, pp. 12-17.
- [28] Jackson, L.A., P.D. Gardner, and L.A. Sullivan, "Engineering Persistence: Past, Present, and Future Factors and Gender Differences," *Higher Education*, Vol. 26, No. 2, 1993, pp. 227-246.
- [29] Eris, O., D. Chachara, H. Chen, C. Rosca, L. Ludlow, S.D. Sheppard, and K. Donaldson, "A Preliminary Analysis of Correlates of Engineering Persistence: Results from a Longitudinal Study," *Proceedings, American Society for Engineering Education Conference*, 2007.
- [30] Hartman, H., and M. Hartman, "Leaving Engineering: Lessons from Rowan University's College of Engineering," *Journal of Engineering Education*, Vol. 95, No. 1, 2006, pp. 49-61.
- [31] Leuwerke, W.C., S. Robbins, R. Sawyer, and M. Hovland, "Predicting Engineering Major Status from Mathematics Achievement and Interest Congruence," *Journal of Career Assessment*, Vol. 12, No. 2, 2004, pp. 135-149.
- [32] Astin, A.W., "Student Involvement: A Developmental Theory for Higher Education," *Journal of College Student Development*, Vol. 40, No. 5, 1999, pp. 518-529.
- [33] Besterfield-Sacre, M., M. Moreno, L.J. Shuman, and C.J. Atman, "Gender and Ethnicity Differences in Freshmen Engineering Student Attitudes: A Cross-institutional Study," *Journal of Engineering Education*, Vol. 9, No. 4, 2001, pp. 477-489.
- [34] American Council on Education, *Minorities in Higher Education 2008: Twenty-third Status Report*, Washington, DC: American Council on Education, 2008.

- [35] Congressional Commission on the Advancement of Women and Minorities in Science, Engineering and Technology Development, *Land of Plenty: Diversity as America's Competitive Edge in Science, Engineering and Technology*, Alexandria, VA: National Science Foundation, 2000.
- [36] Georges, A., "Keeping What We've Got: The Impact of Financial Aid on Minority Retention in Engineering," *NACME Research Letter*, Vol. 9, No.1, 1999, pp. 1-21.
- [37] Lang, M., and C.A. Ford (Eds.), *Strategies for Retaining Minority Students in Higher Education*, Springfield, IL: Charles C. Thomas, 1992.
- [38] May, G.S., and D.E. Chubin, "A Retrospective on Undergraduate Engineering Success for Underrepresented Minority Students," *Journal of Engineering Education*, Vol. 92, No. 1, 2003, pp. 27-39.
- [39] Neisler, O.J., "Access and Retention Strategies in Higher Education: An Introductory Overview," in M. Lang and C. Ford (Eds.), *Strategies for Retaining Minority Students in Higher Education*, Springfield, IL: Charles C. Thomas, 1992, pp. 3-21.
- [40] Sax, L.J., and A.W. Astin, *The Gender Gap in College: Maximizing the Developmental Potential of Women and Men*, Indianapolis, IN: Jossey-Bass, 2008.
- [41] Sayles, A.H., "Diversity: An Engineering Process," *Proceedings, American Society for Engineering Education Annual Conference and Exposition*, West Point, NY, 2004.
- [42] Jackson, S.A., "A Bridge to the Future," Paper presented at the Engineering 2020: Visioning and Scenario-Development Workshop, Woods Hole, MA, 2002.
- [43] Bureau of Labor Statistics, *Occupational Outlook Handbook, 2008-09 Edition*, Washington, DC: United States Department of Labor, 2009.
- [44] Texas State Data Center and Office of the State Demographer, *The Texas Challenge in the Twenty-First Century: Implications of Population Change for the Future of Texas*, San Antonio, TX: Center for Demographic and Socioeconomic Research and Education, 2002.
- [45] "Texas Becomes Nation's Newest 'Majority-Minority' State," URL: <http://www.census.gov/newsroom/releases/archives/population/cb05-118.html>, 2005.

- [46] United States Department of Education, *Crossing the Great Divide: Can We Achieve Equity When Generation Y Goes to College?* Washington, DC: United States Department of Education, 2000.
- [47] Engineering Workforce Commission, *Engineering and Technology Enrollments, Fall 2007*, Elkridge, MD: Engineering Workforce Commission, 2008.
- [48] National Science Foundation, *Women, Minorities, and Persons with Disabilities in Science and Engineering: 2007*, Alexandria, VA: National Science Foundation, Division of Science Resource Statistics, 2007.
- [49] Seymour, E., "Tracking the Processes of Change in U. S. Undergraduate Education in Science, Mathematics, Engineering, and Technology," *Science Education*, Vol. 85, No. 6, 2002, pp. 79-105.
- [50] Allen, D., "Desire to Finish College: An Empirical Link between Motivation and Persistence," *Research in Higher Education*, Vol. 40, No. 4, 1999, pp. 61-85.
- [51] Brown, S. and B.C. Clewell, *Project Talent Flow: The Non-SEM Field Choices of Black and Latino Undergraduates with the Aptitude for Science, Engineering, and Mathematics Careers*, Washington, DC: American Association for the Advancement of Science, 1998.
- [52] Goodman, I.F., C.M. Cunningham, C. Lachapelle, M. Thompson, K. Bittinger, R.T. Brennan, and M. Delci. "Final Report on the Women's Experiences in College Engineering (WECE) Project," Cambridge, MA: Goodman Research Group, 2002.
- [53] United States Department of Education, *Profile of Undergraduates in U.S. Post Secondary Institutions: 1999-2000*, Washington, DC: United States Department of Education, 2002.
- [54] Rogers, S.J., and E.G. Menaghan, "Women's Persistence in Undergraduate Majors: The Effects of Gender Disproportionate Representation," *Gender and Society*, Vol. 5, No. 4, 1991, pp. 549-564.
- [55] Hutchison, M.A., D.K. Follman, M. Sumpter, and G. Bodner, "Factors Influencing the Self-Efficacy Beliefs of First-Year Engineering Students," *Journal of Engineering Education*, Vol. 95, No. 1, 2006, pp. 39-47.
- [56] Castaneda, G.G., and J.L. Winer, "Psychological Models of Engineering Careers: Academic Prediction," Paper presented at the Annual Meeting of the Southwestern Psychological Association, Austin, TX, 1985.

- [57] Ginorio, A., *Warming the Climate for Women in Academic Science*, Washington, DC: Association of American Colleges and Universities, Program on the Status and Education of Women, 1995.
- [58] Wyer, M., "Intending to Stay: Images of Scientists, Attitude toward Women, and Gender as Influences on Persistence among Science and Engineering Majors," *Journal of Women and Minorities in Science and Engineering*, Vol. 9, No. 1, 2003, pp. 1-16.
- [59] Rutter, M., "Psychosocial Resilience and Protective Mechanisms," *American Journal of Orthopsychiatry*, Vol. 57, No. 3, 1987, pp. 316-331.
- [60] Masten, A.S., K. Best, and N. Garmezy, "Resilience and Development: Contributions from the Study of Children Who Overcome Adversity," *Development and Psychopathology*, Vol. 2, No. 4, 1990, pp. 425-444.
- [61] Wang, M. and E. Gordon (Eds.), *Educational Resilience in Inner Cities*, Washington, DC: Office of Educational Research and Improvement, 1993.
- [62] Van Breda, A.D., *Resiliency Theory: A Literature Review*, Pretoria, South Africa: South African Military Health Service, 2001.
- [63] Henderson, N., and M. Milstein, *Resiliency in Schools: Making It Happen for Students and Educators*, Thousand Oaks, CA: Corwin Press, Inc., 2003.
- [64] Winfield, L., *Developing Resilience in Urban Youth*, Oakbrook, IL: North Central Regional Educational Laboratory, 1994.
- [65] Clauss-Ehlers, C., and C. Wibrowski, "Building Educational Resilience and Social Support: The Effects of the Educational Opportunity Fund Program Among First and Second Generation College Students," *Journal of College Student Development*, Vol. 48, No. 5, 2007, pp. 574-584.
- [66] Alva, S.A., "Academic Invulnerability among Mexican-American Students: The Importance of Protective Resources and Appraisals," *Hispanic Journal of Behavioral Sciences*, Vol. 13, No. 1, 1991, pp. 18-34.
- [67] Arellano, A.R., and A.M. Padilla, "Academic Invulnerability among a Select Group of Latino University Students," *Hispanic Journal of Behavioral Sciences*, Vol. 18, No. 4, 1996, pp. 485-508.
- [68] McMillian, J., and D. Reed, *Defying the Odds: A Study of Resilient At-Risk Students*, Richmond, VA: Metropolitan Educational Research Consortium, 1993.
- [69] Anderson, J.A., "Tailoring Assessment to Study Student Learning Styles," *American Association for Higher Education*, Vol. 53, No. 7, 2001, pp. 3-7.

- [70] Felder, R., and L.K. Silverman, "Learning and Teaching Styles in Engineering Education," *Engineering Education*, Vol. 78, No. 7, 1988, pp. 674-681.
- [71] Felder, R., "Matters of Style," *ASEE Prism*, Vol. 6, No. 4, 1996, pp. 18-23.
- [72] Dunn, R., "Understanding the Dunn and Dunn Learning Style Model and the Need for Individual Diagnosis and Prescription," *Reading, Writing, and Learning Disabilities*, Vol. 6, No. 3, 1990, pp. 237-247.
- [73] *Merriam Webster Dictionary On-line*, URL: <http://www.merriam-webster.com/>, accessed on September 4, 2006.
- [74] Anderson, J.A., "Toward a Framework for Matching Teaching and Learning Styles for Diverse Populations," in *The Importance of Learning Styles: Understanding the Implications for Learning, Course Design, and Education*, Westport, CT: Greenwood Press, 1995.
- [75] Cassidy, S., "Learning Styles: An Overview of Theories, Models, and Measures," *Educational Psychology*, Vol. 24, No. 4, 2004, pp. 419-444.
- [76] Coffield, F., D. Moseley, E. Hall, and K. Ecclestone, *Should We Be Using Learning Styles? What Research Has to Say to Practice*, London, England: Learning and Skills Council and the Department for Education and Skills, 2004.
- [77] Ayre, M., and A. Nafalski, "Recognising Diverse Learning Styles in Teaching and Assessment of Electronic Engineers," *Proceedings, ASEE/IEEE Frontiers in Education Conference*, 2000, pp. 18-23.
- [78] Felder, R., and J. Spurlin, "Applications, Reliability and Validity of the Index of Learning Styles," *International Journal of Engineering Education*, Vol. 21, No. 1, 2005, pp. 103-112.
- [79] Felder, R., "Reaching the Second Tier: Learning and Teaching Styles in College Science Education," *Journal of College Science Teaching*, Vol. 23, No. 5, 1993, pp. 286-290.
- [80] Felder, R., and R. Brent, "Understanding Student Differences," *Journal of Engineering Education*, Vol. 94, No. 1, 2005, pp. 57-72.
- [81] Dunn, R., S.A. Griggs, J. Olson, M. Beasley, and B.S. Gorman, "A Meta-Analytic Validation of the Dunn and Dunn Model of Learning-Style Preferences," *The Journal of Educational Research*, Vol. 88, No. 6, 1995, pp. 353-362.
- [82] Dunn, R., *Practical Approaches to Using Learning Styles in Higher Education*, Westport, CT: Bergin & Garvey, 2000.

- [83] Ivie, S.D., "Learning Styles: Humpty Dumpty Revisited," *McGill Journal of Education*, Vol. 44, No. 3, 2009, pp. 177-192.
- [84] Larkin-Hein, T., and D.D. Bundy, "Research on Learning Styles: Applications in the Physics and Engineering Classroom," *IEEE Transactions on Education*, Vol. 44, No. 3, 2001, pp. 276-281.
- [85] Hein, T.L., and D.D. Bundy, "Teaching to Students' Learning Styles: Approaches That Work," *Proceedings, 29th ASEE/IEEE Frontiers in Education Conference*, 1999, pp. 7-14.
- [86] Kolb, A.Y. and D. Kolb, "The Kolb Learning Style Inventory - Version 3.1: 2005 Technical Specifications," URL: www.learningfromexperience.com/images/uploads/Tech_spec_LSI.pdf, accessed on April 10, 2010.
- [87] Ruble, T.L., and D.E. Stout, "Comments on the Use of the LSI in Research on Student Performance in Accounting Courses," *The Accounting Educator's Journal*, Vol. 5, 1993, pp. 35-45.
- [88] Duff, A., and T. Duffy, "The Role of Cognitive Learning Styles in Accounting Education: Developing Learning Competencies," *Journal of Accounting Education*, Vol. 22, No. 1, 2004, pp. 29-52.
- [89] Sheehan, M., and D. Kearns, "Using Kolb: Implementation and Evaluation of Facilitation Skills," *Industrial and Commercial Training*, Vol. 27, No. 6, 1995, pp. 8-14.
- [90] Duff, A., and T. Duffy, "Psychometric Properties of Honey & Mumford's Learning Styles Questionnaire (LSQ)," *Personality and Individual Differences*, Vol. 33, No. 1, 2002, pp. 147-163.
- [91] Smith, J., "Learning Styles: Fashion Fad or Lever for Change? The Application of Learning Style Theory to Inclusive Curriculum Delivery," *Innovations in Education and Teaching International*, Vol. 39, No. 1, 2002, pp. 63-70.
- [92] Honey, P., and A. Mumford, *The Learning Styles Helper's Guide*, Maidenhead, England: Peter Honey Publications Ltd., 2000.
- [93] Allinson, C.W., and J. Hayes, "Validity of the Learning Styles Questionnaire," *Psychological Reports*, Vol. 67, No. 3, 1990, pp. 859-866.
- [94] Allinson, C.W., and J. Hayes, "The Learning Styles Questionnaire: An Alternative to Kolb's Inventory?" *Journal of Management Studies* Vol. 25, No. 3, 1988, pp. 269-281.

- [95] Felder, R., G.N. Felder, and E.J. Dietz, "The Effects of Personality Type on Engineering Student Performance and Attitudes," *Journal of Engineering Education*, Vol. 91, No. 1, 2002, pp. 3-17.
- [96] Pittenger, D.J., "The Utility of the Myers-Briggs Type Indicator," *Review of Educational Research*, Vol. 63, No. 4, 1993, pp. 467-488.
- [97] Boyle, G.J., "Myers-Briggs Type Indicator (MBTI): Some Psychometric Limitations," *Australian Psychologist*, Vol. 30, 1995, pp. 71-74.
- [98] Riding, R.J., and S.G. Rayner, *Cognitive Styles and Learning Strategies: Understanding Style Differences in Learning and Behavior*, London, England: David Fulton, 1998.
- [99] Bonham, B.S., and H.R. Boylan, "A New Look at Learning Styles," *Research in Developmental Education*, Vol. 10, No. 4, 1993, pp. 1-4.
- [100] Brown, E., A. Cristea, C. Stewart, and T. Brailsford, "Patterns in Authoring of Adaptive Educational Hypermedia: A Taxonomy of Learning Styles," *Educational Technology & Society*, Vol. 8, No. 3, 2005, pp. 77-90.
- [101] Severiens, S.E., and G.T.M. Dam, "Gender Differences in Learning Styles: A Narrative Review and Quantitative Meta-analysis," *Higher Education*, Vol. 27, No. 4, 1994, pp. 487-501.
- [102] Hickcox, L.K., "Learning Styles: A Survey of Adult Learning Style Inventory Models," in *The Importance of Learning Styles: Understanding the Implications for Learning, Course Design, and Education*, Westport, CT: Green Publishing, 1995.
- [103] Drysdale, M.T.B., J.L. Ross, and R.A. Schultz, "Cognitive Learning Styles and Academic Performance in 19 First-year University Courses: Successful Students versus Students at Risk," *Journal of Education for at Risk*, Vol. 6, No. 3, 2001, pp. 271-289.
- [104] Krovetz, M., *Fostering Resiliency*, Thousand Oaks, CA: Corwin Press, Inc., 1999.
- [105] Beasley, M., T. Thompson, and J. Davidson, "Resilience in Response to Life Stress: The Effects of Coping Style and Cognitive Hardiness," *Personality and Individual Differences*, Vol. 34, No. 1, 2003, pp. 77-95.
- [106] Misra, R., and M. McKean, "College Students' Academic Stress and Its Relationship to Their Anxiety, Time Management, and Leisure Satisfaction," *American Journal of Health Studies*, Vol. 16, 2000, pp. 41-51.

- [107] Soderstrom, M., C.L. Dolbier, J.A. Leiferman, and M.A. Steinhardt, "The Relationship of Hardiness, Coping Strategies, and Perceived Stress to Symptoms of Illness," *Journal of Behavioral Medicine*, Vol. 23, No. 3, 2000, pp. 311-328.
- [108] Rawson, H.E., K. Bloomer, and A. Kendall, "Stress, Anxiety, Depression, and Physical Illness in College Students," *Journal of Genetic Psychology*, Vol. 155, No. 3, 2001, pp. 321-330.
- [109] Colgate, M.A., *A Secondary Analysis Assessing the Personal Resilience Questionnaire Exploring the Relationships between Resilience and Exercise*, College Park, MD: University of Maryland, College Park, 1995.
- [110] Lazarus, R.S., "From Psychological Stress to the Emotions: A History of Changing Outlooks," *Annual Review of Psychology*, Vol. 44, 1993, pp. 1-21.
- [111] Conner, K.M., and J. Davidson, "Development of a New Resilience Scale: The Conner-Davidson Resilience Scale (CD-RISC)," *Depression and Anxiety*, Vol. 18, No. 2, 2003, pp. 76-82.
- [112] Campbell-Sills, L., and M.B. Stein, "Psychometric Analysis and Refinement of the Connor-Davidson Resilience Scale (CD-RISC): Validation of a 10-item Measure of Resilience," *Journal of Traumatic Stress*, Vol. 20, No. 6, 2007, pp. 1019-1028.
- [113] Neill, J., and K. Dias, "Adventure Education and Resilience: The Double-Edged Sword," *Journal of Adventure Education and Outdoor Learning*, Vol. 2, No. 1, 2001, pp. 35-42.
- [114] Wagnild, G., "A Review of the Resilience Scale," *Journal of Nursing Management*, Vol. 17, No. 2, 2009, pp. 105-113.
- [115] Wagnild, G., and H.M. Young, "Development and Psychometric Evaluation of the Resilience Scale," *Journal of Nursing Management*, Vol. 1, No. 2, 1993, pp. 165-178.
- [116] Conner, D.R., *Managing at the Speed of Change*, New York, NY: Villard Books, 1992.
- [117] Organizational Development Resources, *The Personal Resiliency Profile Handbook*, Atlanta, GA: Organizational Development Resources, 2003.
- [118] Organizational Development Resources, *Criterion-related Validity of the Personal Resilience Questionnaire*, Atlanta, GA: Organizational Development Resources, 1996.

- [119] Bryant, P.C., *Predictive Validity and Test-retest Reliability of a Measure of Resilience*, Atlanta, GA: Georgia Institute of Technology, 1995.
- [120] Aaron, E.N., and A. Aaron, "Sensory-processing Sensitivity and Its Relation to Introversion and Emotionality," *Journal of Personality and Social Psychology*, Vol. 73, No. 2, 1997, pp. 345-368.
- [121] Taylor, L.M., *The Relation between Resilience, Coaching, Coping Skills Training, and Perceived Stress During a Career-threatening Milestone*, Doctoral dissertation, Atlanta, GA: Georgia State University, 1997.
- [122] Office of Institutional Studies and Planning (OISP), *Student Enrollment Profiles, 2006*, College Station, TX: Texas A&M University, 2006.
- [123] "Learning Styles and Strategies," URL: <http://www4.ncsu.edu/unity/lockers/users/f/felder/public/ILSdir/styles.htm>, accessed on January 23, 2009.
- [124] Johnson, D., *Applied Multivariate Methods for Data Analysts*, Belmont, CA: Duxbury Press, 1998.
- [125] Kline, P., *An Easy Guide to Factor Analysis*, London, England: Routledge, 1994.
- [126] Gorsuch, R.L., *Factor Analysis*, Hillsdale, NJ: L. Erlbaum Associates, 1983.
- [127] Comrey, A.L., and H.B. Lee, *A First Course in Factor Analysis*, Hillsdale, NJ: L. Erlbaum Associates, 1992.
- [128] DiStefano, C., M. Zhu, and D. Mindrila, "Computing Factor Scores," *Practical Assessment, Research and Evaluation*, Vol. 14, No. 20, 2009, pp. 1-11.
- [129] Bandura, A., "Self-efficacy: Toward a Unifying Theory of Behavioral Change," *Psychological Review*, Vol. 84, No. 2, 1977, pp. 191-215.
- [130] Bandura, A., *Self-Efficacy: The Exercise of Control*, New York, NY: Freeman, 1997.
- [131] Bong, M., "Comparison between Self-concept and Self-efficacy in Academic Motivation Research," *Educational Psychologist*, Vol. 34, No. 3, 1999, pp. 139-154.
- [132] Jackson, J., "Enhancing Self-efficacy and Learning Performance," *The Journal of Experimental Education*, Vol. 70, No. 3, 2002, pp. 243-255.
- [133] Schunk, D.H., "Self-efficacy and Academic Motivation," *Educational Psychologist*, Vol. 26, No. 3, 1991, pp. 207-231.

- [134] Huang, C.L., "Self-efficacy in the Prediction of Academic Performance of Engineering Students," *Proceedings, American Society for Engineering Education Gulf-Coast Annual Conference*, 2003.
- [135] Lent, R.W., S.D. Brown, and K.C. Larkin, "Self-efficacy in the Prediction of Academic Performance and Perceived Career Options," *Journal of Counseling Psychology*, Vol. 33, No. 3, 1986, pp. 265-269.
- [136] Lent, R.W., S.D. Brown, and K.C. Larkin, "Relation of Self-efficacy Expectations to Academic Achievement and Persistence," *Journal of Counseling Psychology*, Vol. 33, No. 3, 1984, pp. 265-269.
- [137] Hayden, D.C., and E.L. Holloway, "A Longitudinal Study of Attrition among Engineering Students," *Engineering Education*, Vol. 75, No. 7, 1985, pp. 664-669.
- [138] Griffin-Pierson, S., "Achievement and Competitiveness in Women," *Journal of College Student Development*, Vol. 29, No. 6, 1988, pp. 491-495.
- [139] Lent, R.W., and S.D. Brown, "Social Cognitive Approach to Career Development: An Overview," *The Career Development Quarterly*, Vol. 44, No. 4, 1996, pp. 310-321.
- [140] Hergenhahn, B., *An Introduction to Theories of Personality*, Englewood Cliffs, NJ: Prentice Hall, 1994.

APPENDIX A**INDEX OF LEARNING STYLES QUESTIONNAIRE**

For each of the 44 questions below select either "a" or "b" to indicate your answer. Please choose only one answer for each question. If both "a" and "b" seem to apply to you, choose the one that applies more frequently. When you are finished selecting answers to each question please select the submit button at the end of the form.

1. I understand something better after I
 - ☐ (a) try it out.
 - ☐ (b) think it through.
2. I would rather be considered
 - ☐ (a) realistic.
 - ☐ (b) innovative.
3. When I think about what I did yesterday, I am most likely to get
 - ☐ (a) a picture.
 - ☐ (b) words.
4. I tend to
 - ☐ (a) understand details of a subject but may be fuzzy about its overall structure.
 - ☐ (b) understand the overall structure but may be fuzzy about details.
5. When I am learning something new, it helps me to
 - ☐ (a) talk about it.
 - ☐ (b) think about it.
6. If I were a teacher, I would rather teach a course
 - ☐ (a) that deals with facts and real life situations.
 - ☐ (b) that deals with ideas and theories.
7. I prefer to get new information in
 - ☐ (a) pictures, diagrams, graphs, or maps.
 - ☐ (b) written directions or verbal information.
8. Once I understand
 - ☐ (a) all the parts, I understand the whole thing.
 - ☐ (b) the whole thing, I see how the parts fit.
9. In a study group working on difficult material, I am more likely to
 - ☐ (a) jump in and contribute ideas.
 - ☐ (b) sit back and listen.

10. I find it easier
- ☐ (a) to learn facts.
 - ☐ (b) to learn concepts.
11. In a book with lots of pictures and charts, I am likely to
- ☐ (a) look over the pictures and charts carefully.
 - ☐ (b) focus on the written text.
12. When I solve math problems
- ☐ (a) I usually work my way to the solutions one step at a time.
 - ☐ (b) I often just see the solutions but then have to struggle to figure out the steps to get to them.
13. In classes I have taken
- ☐ (a) I have usually gotten to know many of the students.
 - ☐ (b) I have rarely gotten to know many of the students.
14. In reading nonfiction, I prefer
- ☐ (a) something that teaches me new facts or tells me how to do something.
 - ☐ (b) something that gives me new ideas to think about.
15. I like teachers
- ☐ (a) who put a lot of diagrams on the board.
 - ☐ (b) who spend a lot of time explaining.
16. When I'm analyzing a story or a novel
- ☐ (a) I think of the incidents and try to put them together to figure out the themes.
 - ☐ (b) I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.
17. When I start a homework problem, I am more likely to
- ☐ (a) start working on the solution immediately.
 - ☐ (b) try to fully understand the problem first.
18. I prefer the idea of
- ☐ (a) certainty.
 - ☐ (b) theory.
19. I remember best
- ☐ (a) what I see.
 - ☐ (b) what I hear.

20. It is more important to me that an instructor
- ☐ (a) lay out the material in clear sequential steps.
 - ☐ (b) give me an overall picture and relate the material to other subjects.
21. I prefer to study
- ☐ (a) in a study group.
 - ☐ (b) alone.
22. I am more likely to be considered
- ☐ (a) careful about the details of my work.
 - ☐ (b) creative about how to do my work.
23. When I get directions to a new place, I prefer
- ☐ (a) a map.
 - ☐ (b) written instructions.
24. I learn
- ☐ (a) at a fairly regular pace. If I study hard, I'll "get it."
 - ☐ (b) in fits and starts. I'll be totally confused and then suddenly it all "clicks."
25. I would rather first
- ☐ (a) try things out.
 - ☐ (b) think about how I'm going to do it.
26. When I am reading for enjoyment, I like writers to
- ☐ (a) clearly say what they mean.
 - ☐ (b) say things in creative, interesting ways.
27. When I see a diagram or sketch in class, I am most likely to remember
- ☐ (a) the picture.
 - ☐ (b) what the instructor said about it.
28. When considering a body of information, I am more likely to
- ☐ (a) focus on details and miss the big picture.
 - ☐ (b) try to understand the big picture before getting into the details.
29. I more easily remember
- ☐ (a) something I have done.
 - ☐ (b) something I have thought a lot about.
30. When I have to perform a task, I prefer to
- ☐ (a) master one way of doing it.
 - ☐ (b) come up with new ways of doing it.

31. When someone is showing me data, I prefer
- ☐ (a) charts or graphs.
 - ☐ (b) text summarizing the results.
32. When writing a paper, I am more likely to
- ☐ (a) work on (think about or write) the beginning of the paper and progress forward.
 - ☐ (b) work on (think about or write) different parts of the paper and then order them.
33. When I have to work on a group project, I first want to
- ☐ (a) have "group brainstorming" where everyone contributes ideas.
 - ☐ (b) brainstorm individually and then come together as a group to compare ideas.
34. I consider it higher praise to call someone
- ☐ (a) sensible.
 - ☐ (b) imaginative.
35. When I meet people at a party, I am more likely to remember
- ☐ (a) what they looked like.
 - ☐ (b) what they said about themselves.
36. When I am learning a new subject, I prefer to
- ☐ (a) stay focused on that subject, learning as much about it as I can.
 - ☐ (b) try to make connections between that subject and related subjects.
37. I am more likely to be considered
- ☐ (a) outgoing.
 - ☐ (b) reserved.
38. I prefer courses that emphasize
- ☐ (a) concrete material (facts, data).
 - ☐ (b) abstract material (concepts, theories).
39. For entertainment, I would rather
- ☐ (a) watch television.
 - ☐ (b) read a book.
40. Some teachers start their lectures with an outline of what they will cover. Such outlines are
- ☐ (a) somewhat helpful to me.
 - ☐ (b) very helpful to me.

41. The idea of doing homework in groups, with one grade for the entire group,
- ☐ (a) appeals to me.
 - ☐ (b) does not appeal to me.
42. When I am doing long calculations,
- ☐ (a) I tend to repeat all my steps and check my work carefully.
 - ☐ (b) I find checking my work tiresome and have to force myself to do it.
43. I tend to picture places I have been
- ☐ (a) easily and fairly accurately.
 - ☐ (b) with difficulty and without much detail.
44. When solving problems in a group, I would be more likely to
- ☐ (a) think of the steps in the solution process.
 - ☐ (b) think of possible consequences or applications of the solution in a wide range of areas.

APPENDIX B

PERSONAL RESILIENCE QUESTIONNAIRE

SAMPLE ITEMS

The following items are a representation of randomly selected questions from the PRQ.

Task that don't have a simple or clear-cut solution are fun.

I use list to remind me of all the things that need to be done.

I prefer to stick to tried and true clothing styles.

One thing I'm really good at is making sense out of confusing situations.

I feel confused and indecisive when trying to make important decisions in my life.

You should always have a detailed plan before trying to overcome a complex problem.

My friends would gladly help with my transportation or offer a place for me to stay if I ever needed it.

I am not capable to do the things I'd like to do.

I am powerless to change the things in my life.

I am currently working on several things that I am committed to.

VITA

SHANNON DEONNE WALTON

218 Wisenbaker Engineering Center (WERC) | 3405 Texas A&M University (TAMU)
College Station, Texas 77843-3405 | shannon@tamu.edu

EDUCATION

Doctor of Philosophy	Texas A&M University, 2010
Master of Science, Safety Engineering	Texas A&M University, 2001
Bachelor of Science, Industrial Engineering	Texas A&M University, 1999

HONORS AND AWARDS

National Science Foundation, Bridge to the Doctorate (BTD) Fellow, 2003

EXPERIENCE

Texas A&M University, College of Engineering

Associate Director, Academic Development	9/2006 – present
Graduate Assistant, non-teaching	8/2005 – 9/2006
Graduate Assistant, non-teaching	1/2001 – 8/2003

Brazos Valley African American Museum

Executive Director, Bryan, Texas	6/2006 – 9/2006
----------------------------------	-----------------

Shell Oil Company

Intern, Safety and Occupational Health Deer Park, Texas	5/2003 – 8/2003
--	-----------------

British Petroleum (BP)

Intern, Industrial Hygienist Houston, Texas	5/2001 – 8/2001
--	-----------------

RESEARCH AND EDUCATION FUNDING AND MANAGEMENT

Senior Personnel, (Karan Watson – Principal Investigator), “TAMUS LSAMP Bridge to the Doctorate Fellowship, Cohort VI,” National Science Foundation, August 2010 – July 2012

Senior Personnel, (Karan Watson – Principal Investigator), “TAMUS LSAMP Bridges to the Doctorate Fellowship, Cohort V,” National Science Foundation, August 2008 – July 2010

Senior Personnel, (Karan Watson – Principal Investigator), “LSAMP: Texas A&M University System Louis Stokes Alliance for Minority Participation, Phase IV Program,” National Science Foundation, August 2007 – July 2012